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I draw from the identity economics, skill development, network theory, and peer effects literature to advance new research questions around educational attainment. Theoretically, I explore the role of competition between own tastes and social group identity for choices, and I extend the theory to the case of two group influences that may combine or compete. Specifically, I apply the extended theory to adolescent choice of effort in school, when adolescents have a family and peer group. Empirically, I study the impact of family and peers on adolescent attitudes about school and their performance in school, using spatial econometrics. The results show that family educational expectations impact attitudes about school and spill-over through a school by the presence of peer effects in attitudes. The results also show that performance in school is affected by attitudes, that peer effects in performance exist, and that spill-overs from changes in attitudes affect the performance of adolescents in a school. The implication from my study is that programs working with both families and adolescents in a school on attitudes about school can generate positive influence, which spreads over the school social space. I contribute to the literature on identity, skill development, and peer effects drawing research questions from insights of all three, providing a theoretical synthesis, and empirically showing evidence consistent with the role of multiple social constraints on the development of attitudes about school and performance in school.

IDENTITY ECONOMICS AND MALLEABLE CHARACTERISTICS AMONG ADOLESCENTS: A STUDY OF FAMILY AND PEER EFFECTS FOR SCHOOLING ATTITUDES AND PERFORMANCE

by

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CHAPTER I
INTRODUCTION

Identity, skill development, and social networks play important parts in educational success. I draw insights from across the economic literature in each of these subjects to develop new research questions, and I empirically study how families and peers influence adolescent effort in school through their influence on identity and skill development and across social networks. Schooling has long been important in the field of economics.[1] The insight that social influences can affect educational choice has been recognized for some time (Becker 1994; Akerlof 1997; Akerlof and Kranton 2002), but how families and peers impart incentives for effort in school that may combine or compete has not been closely studied.

Consider an adolescent student who has attitudes about school that define their academic aspirations and how they think about their school. These attitudes draw influence from a number of sources: family inputs and transmission of expectations, friends' (or peers') attitudes, environments, and individual aspirations that are possibly independent of social influences. This student takes part in a school social space through social links with peers in the school. As students share their attitudes about school and their parents' plans and goals, attitudes can spill-over handed across social link from social link in the social space.

The primary emphasis of this dissertation is to study how malleable attitudes are shaped by families and peers and how such attitudes, family expectations, and spill-overs affect academic outcomes. I relate attitudes to the noncognitive skill development literature and suggest that attitudes may be influenced by the group identities surrounding an adolescent. Noncognitive skill is a term in the literature used to capture dimensions of skill that IQ tests and achievement test scores miss. Examples of non-cognitive skills noted in the literature are perseverance, impulse control,

1. See Heckman, Lochner, and Todd (2006) for an extensive discussion on the rates of return to schooling. Also, see Becker (1994) for an extensive theoretical treatment of human capital acquisition.

trust, self-efficacy, empathy, motivation, goal setting, behaviors, and more (Heckman and Kautz 2014). Often researchers have used personality scales, such locus of control or conscientiousness, to capture these skills (Humphries and Kosse 2017).

Attitudes with relation to education have been broadly considered a part of noncognitive skills (Lipnevich, Gjicali, and Krumm 2016). In a review, Lipnevich, Gjicali, and Krumm (2016) note that attitudes in general can be stable once set but evidence suggests that various attitudes and beliefs are being shaped through multiple dimensions to include socialization and that interventions may be able to divert negative trajectories. Causal evidence on the role of attitudes for educational outcomes is currently limited. Research has, however, consistently found a positive association between attitudes and educational outcomes (Lipnevich, Gjicali, and Krumm 2016) and there is evidence of a substantial causal effect from noncognitive skills in general on future outcomes linked with education—for example, wages (Heckman and Mosso 2014). Because research into noncognitive skills is relatively new, the literature has not entirely determined all the components or how they relate to each other. Evidence does suggest that in general noncognitive skills produce more skill over time (Cunha and Heckman 2008), but this is still a black box. Thus, in this study I do not attempt to address these important nuances; rather, I focus on attitudes as an established component of noncognitive skills and provide the first step in understanding how both family and peer influences contribute together to their development and then impact academic outcomes.

I contribute to the literature on attitudes and noncognitive skills by theoretically discussing the role social identity may play in the development of attitudes about school and then influence academic outcomes, an area not previously discussed in the literature, and I provide the first study to consider whether there are peer effects in attitudes among adolescents. I suggest that identity economics can inform research on the development of noncognitive skills and their role in academic success. As a secondary emphasis, I draw from the literature to put forward new research questions and theoretically explore the implications group identity has even in the face of individual disagreements with ideals.

The research questions at the center of the empirical analyses in this paper are drawn from the combined insights offered by the identity, skill development, and peer effects literature and are described in a simple model of family and peer group identities. Those questions are as follows: do family educational expectations affect an adolescent's attitudes about school and performance in school, do adolescent attitudes affect performance, do peer effects in schooling attitudes and performance exist, and do peer effects in attitudes and performance create spill-over effects from changes in family expectations. Overall, I study whether there are combined effects from families and peers that are separate from more permanent background characteristics.

To summarize the overall story drawn from the literatue and captured in the theoretical model, an adolescent chooses effort in school, influenced by the ideals on schooling transmitted from the family—educational expectations in my study—and the prototypical behavior—proxies an ideal in the peer group—among peers. In this way, immediate returns to schooling are created through identity utility, as in Akerlof and Kranton (2002). Including families and peers as two social influences slightly extends the framework and implies there are two group inputs to the creation of social incentives for effort rather than only one. Also, it serves to motivate conforming incentives separate from the affects of environments or backgrounds. The key insight here is that if the ideals between groups differ then there are competing social incentives for choice of effort. When families and peers both transmit low educational ideals, then there are strong social incentives for low effort, and when both transmit high ideals, there are strong incentives for high effort. Effort in school is also influenced by an adolescent's malleable characteristics, which I frame as attitudes about school. For the empirics, I use GPA to proxy effort.

I hypothesize that attitudes about school manifest a form of malleable characteristics that are shaped by social group conforming incentives, an adolescent's surrounding environment, and by individual academic aspirations. In turn, they impact academic outcomes. Malleable characteristics may reasonably be both cognitive and noncognitive, but as I will discuss reviewing the literature, cognitive skills may be less shapeable by the adolescent period, while noncognitive skills may be quite shapeable and informed by group ideals. As far as adolescent attitudes about school

are malleable, family and peer attitudes may play a role in shaping them. The literature on noncognitive skill finds "psychic" costs explain underinvestment in education that may be determined by these noncognitive type characteristics (Heckman, Stixrud, and Urzua 2006). Thus, improved attitudes may reduce the cost of effort for the adolescent, thereby improving effort. Empirically, I ask whether attitudes impact school performance, as a proxy for effort, but the literature provides us a sense of why such a relationship may exist and a direction for modeling the input of attitudes. Also, I extend to look at the relationship between later life educational attainment and these shapeable attitudes and performance. This extension also allows exploring a longer term outcome that I relate as measure of long term effort.

Peer groups form a network structure across a school that allow changes in ideals or attitudes to send effects over the network handed across social link from social link. Thus, I study both the impact of family educational expectations on an adolescent's attitudes about school and the spill-over effect that changes in family expectation may have over a school network through the presence of peer effects. Finally, I turn to study whether attitudes may influence performance in school and whether changes in attitudes also spill-over effects on performance through the school social space. From an identity perspective, school peers, or more specifically the peer's one identifies with, may create incentives to conform based on the attitudes and expectations in the group. In this sense, both the schooling attitudes and performance in the group proxy the group identity conforming incentives.

In summary, adolescent attitudes about school may be influenced by family educational expectations and likewise by the typical attitudes in their peer group that form ideals of action.[2] Ultimately, shifts in attitudes among adolescents in school and among families can work together to create large effects across a school if social interaction effects exist around attitudes and performance.

Overall, I find results consistent with a model of family and peer identity influences on attitudes about school and performance in school. I find families and peers influence own-attitudes

2. Norms of action is another way to think of this. I take ideals and norms to be interchangeable here.

about school, and I find that spill-overs in attitudes occur from changes in an adolescent's family expectations. Peer effects exist for schooling attitudes and performance. Own-attitudes strongly and positively influence performance, and spill-overs occur in the network for changes in attitudes and family expectations.

The results suggest that working with both families and students in schools on attitudes about school and education can positively impact performance and send effects across a school network. This study is only a step towards understanding the combined influence of family and peer transmission of educational expectations—or educational ideals. It does, however, suggest that interventions in schools that combine treatments for both families and groups of adolescents in the school, with a focus on attitudes and expectations, can generate strong, positive influence across the school.

To study family and peer effects on adolescent attitudes and performance in school, I first review the literature in economics on identity, skill development, and peer effects. Chapter two provides reviews on each of these literatures and then a discussion to lay out new research questions. I do not attempt to answer all of the questions motivated from the literature in this dissertation—only that related to combined family and peer influence. Therefore, chapter two both motivates the questions for this dissertation and a future research agenda.

In chapter three, I introduce a theoretical extension to Akerlof and Kranton's identity utility framework. I consider two models. In the first, I explore the tradeoff that may occur between social group benefits and one's own personal identity, or one's own tastes, if the group prescriptions for action—or ideals for action—do not agree with one's own tastes. This is a model of conflict between an individual and their primary social group. The person decides how close to be to their group and when they do not agree with the group, they can gain utility by moving away at the expense of utility from social goods. If the cost is too high, then the individual may stay close to the group and suffer the lose of utility from complying with the group ideals. This model suggests that seemingly willing participants of an intervention may have treatment effects dampened by the

group they belong to, if the treatment runs counter to the group ideals and valid alternative groups cannot be offered to replace the group benefits provided by one's current group.

In the second model of chapter three, I explore two group identity influences on the choice of academic effort. This model is an explicit model of adolescent choice of effort when families and peers form two groups imparting social incentives. Both groups create conforming incentives from transmission of ideals. Additionally, drawing from the skill development literature, I build in own-attitudes about school as a malleable characteristic that decreases the cost of effort from school as it increases. Transmission of family and peer ideals also plays a role in producing these attitudes. Because attitudes are malleable during adolescence (discussed later in chapter two), the environments surrounding the adolescent will affect their attitudes, which includes the family and peer identity influences. I derive this model into a classical network based model of peer effects.

Chapter four introduces the data, defines the variables, and describes the empirical methods implemented for this study. The data is from the National Longitudinal Study of Adolescent to Adult Health (Add Health). This data provides detailed social information and friendship nominations within school so that peer networks can be constructed. I use spatial econometrics and directly link the partial effects to the second theoretical model in chapter three. Chapter four covers the estimation methods for the spatial models and describes interpretation of the partial effects. I close chapter four with discussion of the identification requirements for the key variables in the model.

To identify social interaction effects, I use network data with spatial methods (as exposited in econometric theory by Bramoullé, Djebbari, and Fortin 2009, Lee 2007a, and Lee, Liu, and Lin 2010 among others).[3] Spatial models with network data take advantage of the network structure to identify the social interaction effects. I consider two seperate methods for dealing with unobserved heterogeneity that may confound estimates of peer effects—estimation of the correlation in the errors between peers and using peers of peers characteristics as instruments.[4] Additionally,

3. See Epple and Romano (2011) for a thorough review of identification strategies employed in the study of peer effects that are not related to spatial and network data studies.

4. I give discussion of the common issues for estimation of peer effects, such as selection, in a later section.

the partial effects from spatial models easily allow testing for spill-overs in variables of interest. Lesage and Pace (2009) have pointed out that applied work with spatial econometrics has often failed to properly explore the partial effects, which can lead to erroneous inference when testing for spill-over effects.[5] This paper employs the partial effects suggested by Lesage and Pace to study spill-overs from changes in family expectations and changes in attitudes.

In chapter five, I turn to a brief exploration of descriptive relationships. This chapter graphically displays the associations between the key variables of interest to study family and peer influence on performance and attitudes. Also, I show the association between own-attitudes about school and performance in school. Overall, the descriptive analyses are consistent with my expectations from the theory.

I explore the results of the spatial models in chapter six. I present models exploring own-attitudes as the dependent variable and performance in school. Subsequently, I examine the partial effects for each of these models to test for direct effects and spill-over effects resulting from changes in model covariates. Chapter six closes with robustness and extended analyses of the key concepts and estimation results. Finally, in chapter 7 I discuss the results and give last remarks.

5. Ajilore (2015) is the only example I am aware of where spatial econometric partial effects are reported in an applied peer effects study.

CHAPTER II

DERIVING NEW RESEARCH QUESTIONS FROM THE IDENTITY, SKILL DEVELOPMENT, AND PEER EFFECTS LITERATURE

Here I survey the identity economics, skill development, and peer effects literatures and discuss research gaps and questions motivated from a synthesis. These questions are: does family influence reach across networks through the presence of peer effects? Do social groups create lasting influence with impacts on later life economic outcomes? If so, is it through creation of beliefs and ideals, for example "don't be like the out-group", through the production of lasting traits, for example conscientiousness, or both? Finally, under what conditions are peer effects generated? The answers may vary by context and impact the direction of policy and intervention efforts. At this point, the literature cannot provide a full answer to each of these question, but it can shed light on their relevance and point towards a research agenda.

Attitudes have been considered as a component of noncognitive skills in a broad literature on the subject across disciplines (Lipnevich, Gjicali, and Krumm 2016). In this dissertation, I empirically focus on the combined role of family and peer effects on adolescents and provide evidence that both influence attitudes about school. The entire set of research gaps and questions motivated in this chapter serve to set forward a research agenda and as a contribution by way of synthesizing new insights out of multiple literatures. For adolescent development, family and peer effects have been studied separately for some time. Only recently, however, have noncognitive development and social identity influences been considered for adolescent outcomes.

Families and peers may compete or impart similar incentives to adolescents. Peer groups in school form networks. Changes originating at one point in the network may spread effects over the school. Additionally, noncognitive skills, or traits, and social identity are two important elements that may intertwine and motivate the study of attitudes about school. Social iden-

tity incentives—or ideals for action transmitted from groups that once followed produce identity utility—from families and peers create channels for group influence on behavior by establishing a code for action. Noncognitive skills are thought to be malleable into adolescents and young adulthood. Thus, families and peers may influence the development of such traits through transmission of academic expectations and ideals. The broader social network plays a role in this development through spill-over effects. These concepts have yet to be intertwined and studied in the literature.

Noncognitive skills affect life outcomes from the labor market to criminality (Heckman and Mosso 2014). Noncognitive skills are emerging in the literature in recognition that ability is not necessarily a singular dimension nor entirely captured by test scores or intelligence tests. Examples of non-cognitive skills noted in the literature are perseverance, impulse control, trust, self-efficacy, empathy, motivation, goal setting, behaviors, and more (Heckman and Kautz 2014). We may also call these skills characteristics. The literature has used several terms interchangeably. Noncognitive skills among young children and adolescents are malleable (Cunha, Heckman, and Schennach 2010; Heckman and Kautz 2012; Heckman and Mosso 2014). Much attention has been given to the role of parents in the production of these skills, or formation of such characteristics, especially at younger ages. Not much attention has formally been applied to exploring the role of social identity and peer effects on noncognitive skill development.

Social identity forms an important avenue for social incentives often discussed in terms of actions such as effort (Akerlof and Kranton 2000, 2002). Effects from these incentives can spread over a social-network structure, such as in a school. Beyond effort social identity may transmit ideals for behavior over a variety of actions such as attitudes and beliefs about education, career paths, or substance. Moreover, given the malleability of noncognitive skills social group influences are likely important to their development. Families and peers represent two groups that may be especially pertinent, where complementary or competing group identities can exist that impact educational attainment and may partially shape overall development.

Peer groups form networks. Changes originating at one point in the network may spread effects over the network (Belhaj, Bramoullé, and Deroïan 2014). Noncognitive skills, or traits, and

social identity are two important elements that may intertwine. Social identity incentives—or ideals for action that once followed produce identity utility—from groups, such as families and peers, create channels for social influence on behavior by establishing a code for action. Given the shapeablity of noncognitive skills, important groups may influence their development. The broader social network plays a role in this development through spill-over effects. These concepts have yet to be fully intertwined and studied in the literature.

It is an open question whether shocks to group ideals or the composition of noncognitive skills in the group can create spill-over effects across a social-network. The network structure may also play a role in enhancing or mitigating spillovers from changes to ideals. This may especially be true if sub-groups within a network have opposing identities and contain few bridges between the sub-groups. Intervention efforts in one sub-group may fail to diffuse to the next or, worse, create conflict between the groups from resistance to identity change. Negative reaction in a sub-group as a response shocks over networks that potentially threaten the group identity have not been considered anywhere in the literature. However, a combined reading of the identity and network literature suggests this more nuanced hypothesis on social network spillovers.

Because noncognitive skills affect later life outcomes, social identity influence on their development may create lasting effects. Peer effects may have long term effects through formation of lasting characteristics. This a hypothesis yet to be tested in the literature. Yet, another issue arises from studying social identity and peer effects: what are the conditions under which strong causal peer effects are generated? As we will see, this also is not well understood. It may be that sufficient group identification is needed for strong peer effects to be generated.

In this chapter, I first review the literature on identity economics, skill devleopment, and peer effects. The goal of the reviews is to frame what we have learned from each literature. Finally, I discuss the research gaps and questions outlined above in light of the insight from these literatures. The discussion weaves together what we know and do not know from each of these literatures to motivate the theoretical and empirical work of this dissertation. Also, I contribute to the

field by using these three literatures to point out gaps and derive new research directions for continued work.

2.1 Review of the Identity Economics Literature

2.1.1 Identity Theory in Economics

Identity economics—where identity is tied to "sense of self"—formalizes the production of identity utility through choice of action by self and action by others conditional on the structure of social categories, prescriptions for action in each social category, and personal characteristics (Akerlof and Kranton 2000). While admittedly agnostic to the conditions giving rise to ideals that form prescriptions for action, identity theory by Akerlof and Kranton provides a framework to model social constraints resulting from non-monetary payoffs.

In theory, identity economics points to a possible mechanism creating peer effects in education. Akerlof and Kranton (2002) model how personal characteristics can sort a student into a group and this can result in differing incentives for effort. They begin with a high school containing only the classic stereotypes of nerds, jocks, and burnouts. A student is sorted into the jocks or nerds if their personal characteristics are closest to one or the other and into the burnouts if their characteristics are too far from the other groups. Each group exerts differing ideals for effort in school. Once in a group, identity utility increases the closer one's effort aligns with the ideal.

Families and other groups, of course, may also transmit ideals and in essence form another group identity. The effect of multiple group ideals jockeying for position has not been closely studied. Akerlof and Kranton do provide some insight by extending their model of identity in education to consider the role of school policy—or possibly school identity. They suggest that school policy can influence the distribution of group types in the school and the characteristics accepted into group identities that promote effort. This implies that there may be a trade-off between a singular school identity driving high effort for those who belong to it but lower overall effort for a larger share of the school. Alternatively, a more inclusive school identity may not push effort as

high for any one group but reduces the number of opposing groups with low effort. Such tradeoffs may also occur along other dimensions but this a gap in the literature.

Beyond education the identity as incentives concept extends to effort in organizations. Akerlof and Kranton (2005) highlight how individuals can be motivated to give various levels of effort in an organization based on identity payoffs and not simply wages. Non-conformity to standard prescriptions in the labor market may result if taking the alternative choices would decrease one's identity utility. This can lead a rational actor to exhibit behavior opposite what traditional economic models predict.

Research since Akerlof and Kranton's initial work has endeavored to explore how social identities arise. In this sense, elements of social identity become endogenous and develop over multiple periods. Examples of this are found in a growing literature highlighting paths for specific identity formation (Battu, Mwale, and Zenou 2007; Bénabou and Tirole 2011; Bisin et al. 2011a; Darity, Mason, and Stewart 2006; Hanming and Loury 2005; Horst, Kirman, and Teschl 2006).

Much of the theoretical literature on identity has focused on how identities may evolve over time to create long term behavior that can be seemingly irrational. Moreover, these may lead to long term effects from the surrounding group(s) one resides within and is culturally bound to. Discrimination from a majority group to a minority group is theorized to form oppositional identities—group identity opposed to the majority group norms. When the majority holds access, for example, to better jobs, an agent from the minority group is faced with a tradeoff between losing identity utility if adopting majority group norms or losing wages if rejecting the norms. The stronger the discrimination and the stronger the oppositional identity the more likely a person takes wage penalties to avoid identity losses (Battu, Mwale, and Zenou 2007). Bisin et al. (2011a) develop a model showing that racist preference diffusion in the majority culture is a dynamic complement with oppositional identities in the minority culture. As identities become entrenched, members of a group may experience competing incentives where the social becomes increasingly more important.

Theoretically, how identities develop over time affects between group conflict. For example, identity may serve as a mechanism for transmitting personal history in an early period where common identity choice allows risk sharing (Hanming and Loury 2005). The group one is around during this period will be important to the choices one makes in the future. In Hanming and Loury's model, identity choice is impacted by the degree of segregation in social interaction. Sharp cultural differences lead to less interaction between groups and create more separated identity choice. Common choice of identity by people in one group allows different degrees of risk sharing. This can lead to later outcomes such that Pareto improving options are available. Darity, Mason, and Stewart (2006) modeled in-group and out-group altruistic behavior. They show when this behavior is oriented toward one's group but excludes others the long run externalities created can lead to entrenched racial privilege in the market place. Thus, the social groups around people may generate strong effects over time through group interactions that produce identities.

In theory, joint investments in identity by people in society evolve ideals. The social incentives from groups evolve as people move about groups and jointly produce social ideals and values. An individual's choices create externalities on their social groups. The social groups create externalities on the individual, which then lead to changes in both their own and the group's identity and across society as people move about groups (Horst, Kirman, and Teschl 2006). Agents own-choices can result in the development of norms, mores and the variety of social groups existing. Bénabou and Tirole (2011) frame investments in a stock of identity that are responsive to acts, threats, or taboos around beliefs considered to be invaluable. The individual builds their ideal image rather than taking it as given. Norms and mores in society develop out of the interaction of everyone's identity investments. Combined, these theoretical studies imply that the groups which may matter most to an individual's choices are the groups with whom one has the most identity investment and transmission. A point that bears noting in the study of peer effects. Also, this suggests that important groups such as families and one's social network of friends can exert stronger social influence than random groupings.

2.1.2 Experimental Identity Studies in Economics

Experimental evidence indicates that social identity impacts equilibrium selection of effort. Also, it yields both negative and positive effects on a range of outcomes as different social identities become more salient. The group, or groups, that one identifies with matters, giving weight to the hypothesis that peer effects may matter most when there is sufficient group identity. Social incentives are created in part through the identity effects of group membership.

Group identity appears to affect social preferences. One stream of research suggests that this affects one's treatment of others who are either in-group or out-group, particularly when this may create conflict with self-interest (Chen and Li 2009). Chen and Li's study found that participants treated in-group members with greater charity when their payoffs were higher and less envy when lower. Participants also exhibited greater tolerance for bad behavior from in-group than out-group members and extended greater rewards for good behavior. An immediate application of these points is redistribution.

Group belonging influences preferences for redistribution (Klor and Shayo 2010). Even when wealthy Klor and Shayo's participants voted for positive redistribution for their group when their group is poor. When the group is rich and the individual poor, participants voted for low levels of redistribution. The evidence suggests that social identity has a role in determining social preferences. This in turn can impact economic outcomes. Thus, factors interacting with group identity will be important to individual choice. A recent turn in this literature has been to study whether there are heterogeneous effects for in-group/out-group treatment from group belonging.

The degree of group centric behavior towards an out-group exhibits heterogeneity. Kranton et al. (2016) study a lab experiment in a university setting and find some participants behave 'groupy', supporting their own group against others. Some even acted to destroy out-group members income at an expense to themselves, while others did not always respond to group treatment. A set of participants responded to any group division, others only did so under a salient division—political affiliation—, and another set did not change their treatment of others based on group di-

vision. Kranton and Sanders (2017) explores "groupy" behavior with a larger, more representative set of participants and find the previous results are robust. Moreover, they find that "non-groupy" behavior does not correlate with any of the Big-Five personality traits and that "groupy" behavior in the US appears to correlate with areas that have experienced significant negative effects from deindustrialization.

Overall, there appears to be heterogeneity in the effect that group division has on the treatment of out-groups. This may predict how individuals will respond differently to policy shifts and to what degree group belonging will determine social preferences. The research on 'groupy' behavior also implies that some people may respond to peer effects along group divisions more readily while others will not, creating heterogeneity in group effects. An open question, which Kranton and Sanders (2017) point out, is whether group centric behavior becomes more important as people feel their identity is under threat. Moreover, this research also raises a question as to whether intervention or policy efforts to shift social incentives in networks—for instance, in a high school network—can have unintended consequence.

Beyond how one treats in-group and out-group members, social identity affects one's own-outcomes. Benjamin, Choi, and Strickland (2007) find evidence that norms impact discount rates or risk aversion for ethnic and racial identities. Thus, identity may influence outcomes through economic preferences. Social identity effects arise through differing cultural structures nevertheless they can arise as externalities. Two similar studies illustrate this point. Hoff and Pandey (2006) travel to India and study outcomes in performance based games where a cultural identity feature—caste standing—was made salient prior to the games and a control where it was not. They find performance decreased for those with a low caste standing when in the treatment compared to the control when caste standing was not announced. Afridi, Li, and Ren (2015) follow Hoff and Pandey with a similar study design specific to cultural identity elements of migrants around Beijing, China. Their results were largely consistent with Hoff and Pandey's. Identity effects can be both real and persistent across different cultural groups and the effects can be similar. These studies indicate that negative identity features may lead to and reinforce outcomes below ability.

Selection of actions such as effort is yet another choice impacted by social identity in groups. Chen and Chen (2011) find that matching people with in-group members in a multiple-equilibria minimum effort communication game raises their effort level. Relatedly, Gioia (2017) finds that group identity increases the strength of peer effects. Thus, not only does the group one identifies with impact preferences and choice of effort, the peer effects become stronger when matched with fellow in-group members. This further implies that peer effects may be missed when we do not identify the groups that actually matter to a person.

In sum, the experimental evidence implies social identity contributes to the development of preferences and to choices. These influences arise in varying contexts across cultural groups and impact a variety of outcomes. The groups we belong to can create strong incentives determining choice.

2.1.3 Secondary Data Studies of Identity in Economics

The literature studying identity in economics with secondary data is nascent but has still covered a wide range of topics. Many of the papers focus on ethnic identities and the economic assimilation of immigrants in a host nation. Motivating and studying peer effects from identity theory has received less attention and may be a useful direction for new research.

Identity effects may especially impact economic outcomes through education. Prescribed behavior for career or social orientation within social categories has an effect on educational attainment and field of study (Humlum, Kleinjans, and Nielsen 2012). Humlum, Kleinjans, and Nielsen also find that a substantial wage increase is required to compensate an individual for a change from their prescribed career path. Though their study is descriptive, their results are consistent with social identity having a role in the distribution of skills. Also, the impact of multiple group ideals prior to young adulthood may bear strong influence on the final decision to pursue education and particular career paths.

Important group identity incentives may impact the way one thinks about school and both the type and level of education one pursues. Imparted educational ideals impact educational out-

comes and in the aggregate this implies it may influence the evolution of skills for a region or nation. This implication has yet to be examined by the literature. The literature has shed some light on the impact of oppositional identities and the role of education in identity formation.

Oppositional identity formation—theoretically discussed in the literature noted previously—appears to negatively impact educational outcomes in line with theoretical predictions. Blacks and Hispanics in the US who perform too well in school experience negative peer externalities not found among white students (Fryer and Torelli 2010). In the US, having a higher percentage of same race friends increases academic performance among whites but decreases performance among blacks, while parental education enhances the positive effect among whites and mitigates the negative effect among blacks (Patacchini and Zenou 2016). This empirical evidence is consistent with theoretical predictions on the effects of oppositional identity formation within a group that experiences discrimination.

Education policy itself may impact national level, political outcomes through identity. Clots-Figueras and Masella (2013) find, for Catalan language exposure in Spain, that years of compulsory exposure to school instruction in Catalan increased Catalan identity and this increased the probability of choosing a Spanish political party with a Catalan platform. In essence, they argue the language in education reform made ethnic issues more important by increasing Catalan identity.

Kato and Shu (2016) study the role of group identity on quality of work in the presence of workplace production incentives meant to foster competition with data from a textile firm in China. The Chinese Hukou system systematically classifies people into a rural or urban status. Migrant rural workers are known to often face discrimination and rejection from those of an urban status. The authors document how this gives rise to a salient group identification between rural migrant employees at the textile firm and their urban counterparts. Kato and Shu (2016) find that an in-group member's ability level had no effect on a person's quality of work. Out-group member's ability level, however, had a strongly positive effect. They suggest altruism for in-group members may weaken incentive schemes meant to create competition and improve quality of work, while

out-group competition may enhance the incentives from such schemes. This is suggestive, though not generalizable from Kato and Shu's study, that the direction on the influence from group identity will vary with context.

More broadly, some secondary data evidence also supports the role of identity on payoffs and well-being. Using a novel data set drawn from the court records of Nazi Germany, Geerling, Magee, and Brooks (2015) study what equates to a one-shot prisoners dilemma for those accused of high treason under very real and significant payoffs. Some people cooperated with their group and refused information to the Gestapo at all cost. Moreover, the authors find evidence that beliefs, identity, and community can be important in changing payoffs such that individuals cooperate rather than defect even when the stakes are truly high. On well-being, Hetschko, Knabe, and Schöb (2014) study the effect of social identity by examining self-reported well-being changes between reported well-being of the unemployed pre-retirement age and after retirement age. If the identity status for pre-retirement age is to work and post-retirement to not work, then they expected an increase in reported well-being for the unemployed upon retirement age. Their empirical evidence suggests that upon reaching retirement age the unemployed experience a strong increase in subjective well-being. These are, of course, only two results. The empirical identity literature is nascent, but it does point to identity playing a significant role on a broad range of outcomes as its development in theory implies.

A number of studies have focused on ethnic identities and their influence on immigrant outcomes in Europe. Current empirical studies support hypotheses around ethnic identities affecting economics outcomes and the impact of immigrants' acculturation as an important factor in their outcomes (Casey and Dustmann 2010; Constant and Zimmermann 2008; Bisin et al. 2010; Bisin et al. 2011a; Berry et al. 2006; Schüller 2015; Zimmermann, Constant, and Schüller 2014). Many of these studies have focused on immigrants in Germany and it is not clear whether the results are generalizable. I focus only on those related to education and labor market outcomes.

In brief, immigrant parents are important in the formation of their children's identity and their educational and labor market outcomes. For immigrants in Germany, parents have been

found to be important in the formation of their children's identity, and some evidence points to positive labor market effects from home nation identity for immigrant children that may relate to ethnic network effects (Casey and Dustmann 2010). German identity for immigrants, working mostly through mothers, appears to have positive effects on educational outcomes for the children, while for fathers it is minority identity transmission that has some positive effects on education potentially through improving self-esteem (Schüller 2015). Stronger ethnic identity in the aggregate, however, has some negative effects on the labor market outcomes of immigrants in Europe (Bisin et al. 2011a). Bisin et al. (2011a) also find that host nation labor market policies promoting flexible labor markets can mitigate the negative effect of ethnic identity, except when it is very strong.

Social groups and identity incentives appear to be important to a range of outcomes. The strength of those incentives may be quite high, though the literature cannot yet quantify and predict just how high and when they are most pertinent. The early work in empirical identity economics indicates that beliefs, identity, and community form strong incentives for educational decisions, to the decision to stay loyal to one's group at all cost, to the production of well-being, and to labor market outcomes.

2.2 Review of the Skill Development Literature

Skill development is not merely cognitive. Noncognitive skill development matters too. Moreover, environments and investments at different points of the life cycle matter to the development of cognitive and noncognitive skill. Noncognitive skill encompasses a wide array of characteristics, or traits, that develop over time rather than existing as fixed points. Below I note what we have learned from this literature. An understanding of the influence noncognitive development has on later life outcomes, will open a richer framework to explore the lasting influence of groups and social identity at various life stages. These lessons have yet to be combined, which is, in part, the point of this paper.

Character and personality traits that may be considered soft skills, or noncognitive skills, are highly important and, until relatively recently, were often overlooked in the assessment of skill

development. Soft skills get returns in the labor market and they are, in general, associated with future life success (Heckman and Kautz 2012). As noted in the introduction, these skills have been found to consist of perseverance, impulse control, trust, self-efficacy, empathy, motivation, goal setting, and many more (Heckman and Kautz 2014). Some of these deal with how well one can control themselves and others relate to the very attitudes one forms about activities such as work and education. During early life, cognitive and noncognitive skills are developing together. Heckman, Stixrud, and Urzua (2006), however, find it is important to consider them separately, as measures of cognitive skill—IQ tests and achievement scores—fail to capture the role of noncognitive skills in determining future wages and a number of other life outcomes.

Heckman (2008) make the point that research on human development indicates it is a mistake to see nature versus nurture as mutually exclusive. The two are overlapping arenas that produce abilities. The context of abilities that affect future outcomes in both education and other areas is explicitly plural rather than the singular focus on achievement test scores that has become the measuring stick by which many teachers are graded. C. K. Jackson (2012) finds that a noncognitive ability factor associated with a 9th grade teacher effect was important to high-school completion and college attendance and explained a significant amount of variability that test scores did not. Achievement test scores explain only a small part of the variance in long-term outcomes, while character traits are important to educational, labor market, and criminality outcomes among others as well (Heckman and Kautz 2014).

Noncognitive skills are just as important as cognitive skills. Heckman and Mosso (2014) discuss broad evidence from the literature on skill development that show noncognitive skills support cognitive skills. Heckman, Pinto, and Savelyev (2013) examine the mechanisms through which the Perry Preschool program impacted adult outcomes focusing on the channels of cognition, externalizing behaviors, and academic motivation. The Perry program was an early intervention (begun at age 3) targeted at disadvantaged children in an African-American community. It aimed to assist with the development of cognitive and noncognitive skills, and it followed up with both those who were enrolled, and a control group who were not, until age 40. The effects

were significant reductions in future criminal activity, poor health behaviors, and more positive labor market outcomes. Heckman, Pinto, and Savelyev (2013) find that the strongest effects ran through a reduction in externalizing behaviors—aggression, being antisocial, and rule-breaking. While IQ was not strongly affected in the long-run, achievement test scores and academic motivation increased. The program increased life success for the treated even though cognition was not a large part of the gains.

A literature has emerged tearing down notions of skill fixed by genetics. This literature highlights the role of environments throughout the life-cycle in developing both cognitive and noncognitive skill sets that are vital for academic and life success. For disadvantaged children, intervention costs rise with age because effectively shifting skills becomes more difficult (Heckman 2008). Earlier interventions may be able to target both cognitive development and character traits that are valuable in the labor market but after the age of 10 IQ becomes stable, while character and personality are still malleable throughout the teenage and young adult years (Cunha, Heckman, and Schennach 2010; Heckman and Mosso 2014). Economic inequalities can arise and persist through the existence of inequalities in early life that shape a person's skill sets (Heckman and Kautz 2014). Gaps in skill open early and effects from genes are correlated with environments pointing to the conclusion that better environments correspond with better genetic outcomes, thus educational outcomes may partly be a result of inherited environments (Heckman and Mosso 2014). The literature, however, has yet to ask how early life developments can sort one into differing group identities that may improve or worsen trajectories for later life outcomes.

The earlier the intervention the more effective environmental shaping from the intervention can be, as the period for trait development is longer. Chetty, Hendren, and Katz (2016) evaluates age at time of move effects from the Moving to Opportunity (MTO) experiment. This experiment randomly assigned some families a voucher to move out of a low-poverty area. Moving prior to the age of 13, compared to those 13 and older, was found to have significant effects on future economic outcomes. These outcomes include earnings, college attendance, college quality, and neighborhood quality. Furthermore, they find the effect of treament dimished for every year

older at the time of the move. These findings are in harmony with those of Chetty and Hendren (2015) who study families moving over US counties. Their work finds children moving to better counties—on economic and social measures—experienced increasing improvements in future outcomes for every year of exposure. More specific to skills, (Cunha and Heckman 2008) show that both cognitive and noncognitive skill development during childhood is dynamic. Both sets of skills developed during very early life have some influence on their production later in childhood. However, cognitive skills become set much sooner than the noncognitive and it appears to be the noncognitive skills that remain the most malleable for the longest. Thus, interventions affecting noncognitive skills early in life have a longer follow up for their dynamic influence to continue building these skills.

A deeper look at skill development unveils the importance of the family and surrounding environments to the production of multiple abilities. Disadvantaged families have less resources. Less resources applied to child development can hinder both cognitive and noncognitive development (Heckman 2008). The disadvantage is thereby reinforced potentially creating traps difficult to escape.

Family resources as a source of disadvantage are not merely represented by credit constraints. Long-term credit constraints may play some role in development, as it diminishes the ability for investments later in the child's life, but family income is likely to capture a variety of environmental effects such as parental ability, education, and peers that can strongly effect the development of skills (Heckman and Mosso 2014). This point foreshadows my broader suggestion that groups and identity play a role in skill development and that peer effects will inform us how such development may spread over social networks. Family effects may build noncognitive characteristics that then flow over a network through social interaction effects. However, this remains to be explored.

Heckman (2008) indicate that disadvantaged children often face the most negative environments with regard to parental health behaviors and that less educated mothers give less time to activities for their children's learning enrichment. Heckman and Mosso (2014) point out research

that finds mothers of a socio-economic disadvantage typically underestimate the impact of investing in child development. Also, Carneiro, Meghir, and Parey (2013) find evidence that maternal education impacts cognitive skill and especially behavioral problems, implying children of poorly educated mothers may develop skill disadvantages over time.

Time inputs to a child's development are highly important. Maternal time inputs to children's development during early childhood positively affects cognitive and noncognitive skills, effects that show persistence into later periods (Bono et al. 2016). Time investments into children by both parents have been found to play significant roles in cognitive development. These roles appear to diminish with the age of the child highlighting the importance of early life developmental inputs (Boca, Flinn, and Wiswall 2014). Furthermore, some research has emerged that indicates brain development is dramatically diminished if a child experiences social and intellectual neglect early in their life (Heckman 2008).

Given the importance of early life environments and the continued malleability of personality and character traits through adolescences, models with only two periods of human development miss critical junctures in the life cycle (Cunha and Heckman 2007). Theoretical predictions which take into account more than two periods along with the empirical evidence suggest investments and endowments are dynamic complements and even substitutes at a very early age (Heckman and Mosso 2014). Early investments complement with endowments to magnify the development of skill sets in later periods of childhood. This implies the timing of investments is important. Parental skill in timing investments to their children's development at critical points can establish intergenerational links in skill sets even without serious long-term credit constraints (Heckman and Mosso 2014). Long term constraints compound the disadvantage.

Later life investments and interventions are less effective at skill development, but this does not mean it is too late for those who lacked early life investments. Adolescent interventions can help re-gain some of what is lost because of early childhood disadvantage (Heckman and Mosso 2014). Heckman and Mosso particularly point out that successful interventions are ones which support personality and character trait skill development—such as discipline and confidence—

through mentorship, guidance, and offering information. Additionally and importantly, they note that those interventions must not bore or discourage. Furthermore, Sampson (2016) argues that institutional responses play a role in the worsening or improvement of gaps in anti-social and socio-emotional skills. Early life disadvantage can produce poor noncognitive skill among adolescents. Behaviors during adolescence caused by these developed skills lead to a response by institutions that can worsen the trajectory or reinforce the noncognitive disadvantage. Young adult development then follows a similar process. He argues that while the emphasis on early life interventions is surely appropriate, it is not necessarily too late to intervene much later in life. It remains for empirical studies to test for causal effects from later life interventions or from policy shifts in institutional responses.

In sum, the literature on noncognitive skill suggests that characteristics and traits are malleable through the adolescent period and that the development of these skills have important influence on a variety of life outcomes. While much of the focus from a policy perspective has been to suggest early life intervention, it is also apparent that during adolescence a variety of inputs may affect noncognitive characteristics that form beliefs, attitudes and traits. These may then be passed to surrounding group members or from those members. Families for one and peers for another may play roles in this story. The evolution of ideals for action and skills of surrounding group members will then be important to the noncognitive development process. Peer effects on networks may help us understand how such skills spread or even create resistance to interventions seeking to divert their trajectories.

2.3 Review of the Peer Effects Literature

The peer effects literature is an extensive literature. I will not attempt a comprehensive review.[1] Identification issues have been formidable, but the literature is gaining ground towards the identification of peer effects on different dimensions. There are two emerging areas of work that have not been directly pointed out. One asks whether there are peer effects at clearly divisible

1. See Epple and Romano (2011) and Sacerdote (2014) for extensive reviews.

grouping levels such as a dorm, a classroom, or class. This may be of interest on two related fronts: do peer effects at these levels exist and can policy manipulate groupings to improve outcomes. The second area explores peer effects along lines where group identification is more distinct such as nominated friends or groupings along salient identity features—common in the experimental literature. The policy implications may be less about manipulation and more about understanding whether social interaction effects create spillovers and how these channels can be used to effectively diffuse information. This literature is also more closely linked with a literature in network theory.

It is not clear whether these two areas of peer effect studies are measuring the same type of group effects. Moreover, when studies of the first type fail to find peer effects it is rarely discussed whether this is evidence against peer effects or for the lack of group identification. Both types of studies provide useful insight. How they relate and do not should be clearly identified.

The study of peer effects within the first type—as I have defined it—can be sorted into sets. Sacerdote (2014) presents the following: studies exploring an exogenous shift of peoples from an event or policy (for example Hurricane Katrina or the Boston METCO program), studies that take advantage of random variation across cohorts within a school, random assignment of college roommates or dormmates, and designed experiments. Sacerdote provides a review of the findings in each of these arenas of study. To summarize, peer effects appear to exist; however, the literature does not yet offer a consensus on how these effects vary by context, which peers matter the most and when, and what outcomes are truly impacted by peers. Many studies find no effects from average peer ability on test scores, while some do. Non-linear peer effects do appear to exist, such as differing influence from peers across the ability distribution, but we are still not clear on precisely how to take advantage of this or whether this result differs by context. One example of this heterogeneity is evidence that high ability students benefit from high ability peers but low ability students are hindered by high ability peers. Additionally, behavioral and social outcomes consistently return stronger peer effects.

Sacerdote (2014) also provides a thorough discussion of the identification challenges, and the various strategies implemented in this literature. Self-selection into groups, neighborhoods, schools, and the like poses a challenge to causal inference from any correlation between a person's outcomes and the groups they belong to. This point is likely even more concerning for studies based on salient group identification. Manski (1993) presented peer effects in three components: correlated effects from shared environments or similar characteristics among peers, contextual effects from peer backgrounds, and endogenous effects from peer outcomes. The presence of correlated effects introduces an identification problem. Additionally, Manksi illustrated that in the classic linear-in-means model the endogenous effect cannot be separated from the contextual effects even in the absence of correlated effects (the well known "reflection" problem). This does not necessarily hold in models of non-linear peer effects.

The "reflection problem" results from lack of variation in groups. When individual's in the data all share the same group, or are split between a small number of groups, the peer means entering the linear-in-means specification do not vary. Most studies, as a result, have focused on attempts to identify the reduced form peer effect (endogenous and contextual effects combined) from the correlated effects. Lee (2007a) and Bramoullé, Djebbari, and Fortin (2009) show that we can break the "reflection problem" when there is sufficient variation in peer group means. The central insight here is that when group means do not vary much a collinearity problem arises yielding the "reflection problem". This has prompted more work with network based data and studies of the second type discussed above. Other concerns with estimating peer effects include measurement error and peer group selection.

Measurement error is another threat to the estimation of peer effects. Angrist (2014) indicates that in the case of peer effects measurement error can actually result in an upward bias, or overestimation. Feld and Zölitz (2017) highlight, in the context of ability, that the upward bias derives from mismeasured ability, implying not only is own-ability mismeasured but so to is peer ability. When group assignment is "systematic", measurment error generates an overestimation of peer effects when, for example, individuals group together by ability. Feld and Zölitz extend

Angrist's intution to show that when group assignment is random correlation in ability by grouping will be zero. In the random assignment case, measurement error in ability creates the classical measurement error problem and leads to peer effect estimates that are attenuated.

Individual characteristics may lead to groupings that will drive upward bias in the peer effects even in the presence of a random sorting at some level (such as the class). Feld and Zölitz (2017) study peer effects on grades among students at a university in the Netherlands who were assigned randomly to sections within a course. Course selection, however, was nonrandom potentially resulting in groupings at the course level. They eliminate upward measurement error bias by controlling for course fixed effects, which they note removes correlation between individual abilities that may result from the course level grouping. Their empirical results found a significant but quite small positive peer effect. They also found that low ability students were actually hindered by high ability peers. This study fits within my first grouping of peer effect studies. It further suggests manipulation of groupings where group identification may not hold will not result in any economically significant results, at least on the average.

The second type of peer effect studies typically employ spatial models with network data. Beginning with an assumption of exogenous network formation, spatial models and network data break-down the non-linearity introduced by including a spatial lag of the dependent variable and/or a correlation component in the error term and return the structural parameters (Lee 2007a and Bramoullé, Djebbari, and Fortin 2009). Estimators in the spatial literature have been developed with quasi-maximum likelihood, GMM, and two stage least squares (see Kelejian and Prucha (1998), Lee (2003), Lee (2004) Lee (2007b), and Kelejian and Prucha (2010) for examples and more information). Linear dependence between endogenous and contextual effects is broken when there exist sets of individual's who share links but are not linked to each other (Bramoullé, Djebbari, and Fortin 2009). The more variation there is in the peer reference groups the stronger the identification.

Bramoullé, Djebbari, and Fortin (2009) formally develop the use of peers of peers in network data as instruments for the endogenous peer effect. The network architecture provides the

identification restrictions, whereby peers of peers influence a person only through their influence on that person's direct peers. Although, a concern is that identification rests on mathematical structure and assumptions, which may or may not hold (Sacerdote 2014). Moreover, Blume, Brock, and Durlauf (2015) shows that for an assumption of exogenous network formation knowledge of who is not linked together in a network is key to identification and when this condition is met identification holds. Of course, this information may be unobserved, even with friendship nominations, and peer effect estimates with the observed nominations may result in peer group selection effects. Put another way unobserved correlated effects resulting from self-selection into peer groups—or endogenous network formation—and shared environments still render an identification problem for spatial models applied to peer effects.

Lee, Liu, and Lin (2010) introduce a spatial model that controls for group level fixed effects (shared environments) and controls for the spatial correlation in the error terms. They suggest controlling for this correlation may capture variation due to omitted variables representing the peer group selection process. However, we cannot know for sure that it captures all such variation, rather they suggest it as step in the right direction. Lin (2010) uses their method with data from The National Longitudinal Study of Adolescent to Adult Health (Add Health) to study linear-in-mean peer effects in grade point average.

Add Health provides friendship nominations in schools. This allows constructing school networks that capture both direct and indirect links to an individual. It also means that the peer group varies by individual and is the group an adolescent claims to identify with, rather than a group they are assumed to interact within. Of course, in this context peer selection is an even greater problem. Lin (2010) finds strong peer effects from average peer school performance. Her result applies to a small set of peers whom one identifies with. If one believes her estimates, then peer effects may be strong from the individuals who matter to the person. This fits with the experimental findings of Gioia (2017), covered previously, who finds peer effects to be stronger when from a group a person identifies with.

A number of peer effect studies have explored the Add Health data. Calvo–Armengol and Jackson (2009) test game theoretic predictions around the Bonanich-Katz centrality (measure of network centrality incorporating both direct and indirect links) that provide a profile of Nash Equilibrium. They use self-reported high school grade point average, finding evidence positive peer effects increasing in one's centrality. Keeping with the education theme, Patachini, Rainone, and Zenou (2016) find evidence of long lasting peer effects on educational attainment with the Add Health data. Moreover, they take advantage of follow-up peer nominations collected in the second wave for a small subset of the data, showing that it is the long-term peers who matter for long-term effects.

Risky behaviors too have also been studied with Add Health data. Lin (2015), using the econometric estimator in Lee, Liu, and Lin (2010), finds a positive relationship for adolescents between own action and peers' actions regarding risky behaviors such as alcohol consumption and drug use. She also tests multiple iterations of defining peers by exploring a reciprocity assumption[2] and taking advantage of questions about the frequency of activities with each nominated friend. She finds consistently that peer effects from nominated friends are strongest and return the best fit of the data. Fortin and Yazbeck (2015) use spatial methods to model peer effects in fast food consumption, finding evidence for social multiplier effects in fast food consumption. Ajilore (2015) uses spatial methods to explore peer effects from nominated peers on risky sexual behaviors, finding a positive relationship.

Endogenous network formation still lurks in the background as a potential problem with interpreting peer effects in studies with network data. A number of recent econometric papers have suggested methods to better address network formation (Auerbach 2016; Goldsmith-Pinkham and Imbens 2013; Hsieh and Lee 2016; Johnsson and Moon 2015). These studies attempt to establish peer effect estimates with network data free of selection bias by jointly modeling the link

2. The reciprocity assumption assumes a link for persion i to person k if k nominates i regardless of whether i nominated person k or not.

decision between individuals (nodes) and the peer effect. In practice, some of these estimators can be computationally burdensome, especially in the first step, and limit the sample selection.

Goldsmith-Pinkham and Imbens (2013) and Hsieh and Lee (2016) establish identification under parametric modeling. The general principal is to control out unobservable determinants of social-link selection and the outcome being studied. With Add Health data and friendship nominations defining the peer group, (Goldsmith-Pinkham and Imbens 2013) do not find evidence of bias from network formation on the peer effect from school grades. (Hsieh and Lee 2016), using the same data, do find some upward bias in the peer effect; however, they still find significant and positive peer effects from peer grades that are entirely consistent with the model assuming exogenous network formation. Their model is computationally intensive and places a number of restrictions on the data potentially limiting its practical use. Another potential limitation, is that underlying the Hsieh and Lee approach is an assumption on the joint normality of the errors between the network link model and the outcome model of peer effects. Hasselt (2011) shows that in the case of the classic sample selection model results can differ substantially when departures from joint normality are accounted for.

Recently, two new approaches for estimating peer effects with social network data have developed non-parametric methods. Johnsson and Moon (2015) allow the functional form of unobservables entering the peer effect model to be unspecified and fitted by the data, thus they avoid the assumption of joint-normality in Hsieh and Lee (2016). They establish a semi-parametric two-stage estimator that utilizes a non-parametric estimation of the control function entering the second stage estimation of peer effects. Thus, the second stage is conditioned upon the unobservable fixed effect that determines link formation in a flexible manner. Additionally, they estabalish asymptotic results for the estimator. Their identification assumptions are still parametric in nature. Auerbach (2016) takes a fully non-parametric approach to identification, establishing identification in a matching type estimator based on matching pairs of individuals who have a similar distribution of network links. One potential limitation, which he points out, is that his estimator performs better with denser networks.

In general, the evidence in the literature suggests that peer effects do matter and that they matter more for social behaviors than test scores, while the strength of peer effects is not clearly established. There is still more work to be done before we can use the peer effects literature as a guide for policy (Sacerdote 2014).

Overall, studies using nominated friendships to establish the peer group networks point towards strong peer effects emananting from peers one actually identifies with. A new area of research is to directly deal with the possible confounding influence from endogenous network formation in peer effect estimation. This approach requires carefully dealing with the determinants of network formation. The early results suggest that peer effects indeed matter—at least on school performance—after controlling for unobservables related to network formation (Goldsmith-Pinkham and Imbens 2013; Hsieh and Lee 2016). The estimators to this point have a number of limitations. New semi- and non-parametric estimators have recently been introduced to relax certain assumptions crucial to identification made in the previous attempts to handle endogenous network formation. However, we do not yet know how well these estimators can be applied to actual research questions and what results they will return.

Overall, the literature accounting for endogenous network formation is very young. It first requires adequate estimation of group formation. An emerging area of study is to empirically focus directly on the network formation process (Graham 2015). Estimation challenges can be substantial and a fair amount of theoretical econometric work is still to be done. However, given the myriad problems and difficulty with interpreting peer effects, the literature to some extent has placed the cart before the horse. Without a better understanding on how social networks actually form in varying contexts, it will be difficult to do much, from a policy standpoint, with our current evidence on peer effects for outcomes of interest.

2.4 Research Questions and Discussion

I put forward a set of questions and directions from a synthesis of the identity, skill development, and peer effect literatures. Do family and peer effects interact as differing group influ-

ence in ways that combine or compete? Do social group effects create lasting influences? If so, is it through creation of beliefs or a production of lasting characteristics? Finally, under what conditions are peer effects truly generated?

Policy recommendations have been made in the skill development literature but we are not there yet in the identity and peer effect literatures. As Sacerdote (2014) points out, the safe move may be to use what we learn in interventions that attempt to impact non-treated social-network members through social links with the treated. This still requires a better understanding of how spillovers actually spread over networks and moveble dimensions generate spillovers on outcomes of interest. I suggest that research drawing from the three main literatures discussed in this paper is a step in that direction. Because of the malleability of noncognitive skills during childhood and adolescence, identity, skill development, and peer effects will be overlapping sets during these periods. Understanding how all three work and interact will better our ability to construct workable interventions that take advantage of existing channels of social effects.

Family and peer effects may interact through identity incentives and create effects that spillover through a peer network. This process is likely important during childhood and adolescence. It can create social incentives affecting choices. It may also play a role in building noncognitive skills that become lasting traits.

Family background itself is known to be one of the most important factors explaining children's educational attainment, but there are still significant gaps in our knowledge of what composes those effects (Björklund and Salvanes 2011). The skill development literature suggests that early childhood parental investments matter. These investments are often very ad hoc indexes formed from questions such as the number of books in the home (Cunha and Heckman 2008; Todd and Wolpin 2007). More work can be done to explore varying types of parental effort in skill development, such as transmission of beliefs, in-school involvement, in-home involvement, and heterogeneity in types of investments across socio-economic and cultural groups.

Peers form networks, such as a social network within a school or neighborhood. Where peer influence exists, changes in family ideals and investments in child development may spillover

in the network. Therefore, family identity incentives can be magnified through a school social space in the presence of peer effects running across social links.

There is some early evidence in the literature consistent with an interaction of family and peer effects. Avvisati et al. (2014) test the treatment effects of an experiment among disadvantaged Parisian schools. Treated parents came to the school for a series of trainings that attempted to better their ability to guide their children and to improve their attitudes about the school. They found children of treated parents experienced positive treatment effects on a range of outcomes and that untreated children in the same classroom experienced positive indirect effects. Fruehwirth (2016) studies spillovers from parental education at the classroom level among elementary school students. She finds that spillovers from peer parental education exist and differ by parental educational level and across math and reading skill acquisition. Furthermore, she finds that classroom practices by teachers may be sensitive to parental involvement in ways that vary by parental educational level. In turn, this affects all the children in the classroom, though not necessary to the benefit of all types of children in the class.

Family influence may impact the child (or adolescent) and indirectly impact the social links of the child. A research question is whether interventions which work with both families and peer groups on a similar treatment will generate even stronger effects by taking advantage of the social channels between both groups. Alternatively, efforts in one sub-group of the network may work to generate more divisions and opposing identities rather than positive spillovers throughout.

This combination of interventions between families and peers may be especially pertinent if affecting one group will only place them in conflict with another group. The intervention may still yield positive benefits, but the conflict may weaken the positive impacts or even reduce them to zero. The theoretical identity literature predicts that oppositional identities are salient in the face of tradeoffs—for example, when adopting the majority norms requires giving up the minority norms. Therefore, any intervention working with one group must consider how the changes it proposes may be mitigated if those changes run counter to competing group identity influence.

Social identity incentives are determined by the groups one identifies with. Families may transmit ideals for action. Once in a peer group, peers may transmit ideals for action. This joint belonging may combine or compete and create utility incentives to conform with each group. The empirical identity literature indicates that group identity can exert influence on a multitude of choices from effort to risky behaviors to treatment of others and more. The skill development literature indicates that skill gaps open early in both congitive and noncognitive abilities, that cognitive abilities become set by age 10 but noncogntive abilities remain malleable much longer, and that both types of skill impact later life outcomes. The peer effects literature indicates, though still fuzzy on the details, that peers exert influence and that influence appears strongest on social choices rather than test scores. The groups one belongs to yield social utility incentives for behavior that for children and adolescents take place during a time of cognitive and noncognitive skill development.

Something as simple as attitudes and beliefs about the benefits of education may play a role in determining choice of effort and building noncognitive traits, such as the "grit" that Heckman and his colleagues speak so much of. Whether interventions can target skill-development through targeting attitudes, beliefs, and ideals within groups is an open question for future research. Conversely, it may be that interventions can target identity conforming incentives from attitudes, beliefs, and ideals by targeting noncognitive skill development. Do social groups, however, create lasting influences?

Lasting influence from social groups may work through forming beliefs that carry over into later periods, development of noncognitive skills that affect one's productivity, and the networks one has to draw upon for jobs and support. Patachini, Rainone, and Zenou (2016) connect their study of long term peer effects on educational attainment to the formation of beliefs on the returns to education within groups based on the information available to the group. This formation of beliefs impacts educational choices for an individual in the group, which then impacts final educational attainment.

Given the lessons from the skill development literature on the malleability of skills, social groups may influence the production of skills. Once skills become more or less set, the skill development literature provides evidence that they influence later life economic outcomes. Social groups during childhood and adolescence may generate lasting effects through cognitive and noncognitive skill development. Under this hypothesis, effectively controlling for skills in the important social groups should capture some of the family and peer effects on later life outcomes, if any exist. Theory tangentially consistent with this stems from Buechel, Hellmann, and Pichler (2014) and Calvo–Armengol and Jackson (2009) who model how networks are highly important in the passage of cultural traits across generations. Agents who gain benefits from passing on certain traits have incentives to strengthen ties with some networks and not with others. The network provides a plethora of benefits potentially making it difficult for the individual to select opposing traits.

Networks provide information on jobs and resources to rely upon. Letki and Mieri (2015) empirically find evidence indicating even resource poor networks provide greater benefits than being isolated. Also, they find that those of a lower socio-economic standing rely more heavily on their networks despite the fact that their networks are resource poor. In a broad literature review, Perkins, Subramanian, and Christakis (2015) suggest networks create avenues for spreading beliefs, behaviors, and emotions along with financial help, job opportunities, information, and other community resources. Thus, social groups may create lasting influence through the provision of the network resources an individual can draw upon.

Whether and how social groups create lasting causal influence remains an open question. Future work can draw from the literature reviewed here and study affects on later life outcomes from formation of beliefs, the malleability of skills, and the resources a network provides. How interventions are best targeted may depend on which of these channels is salient in a given context. Efforts to improve information on returns to education may alter beliefs developed in groups. Efforts to improve skill development may need to take all of the important social groups into consideration to be effective and consider institutional responses to behaviors (Sampson 2016). Ef-

forts to shift the basic set of resources available to networks may be able to alter long-term network effects. Research on each of these points is needed to draw any conclusions on the effectiveness of each channel. For network resources, positive shifts may dynamically interact with the development of beliefs and skills in the network, implying positive network resource shifts may be dynamic complements with later period interventions focused on network level information and noncognitive development.

Finally, under what conditions are peer effects generated? Studies using network data use very small peer groups of nominated friends. At the larger group level, class or cohort, effects from norm transmission may be small or even non-existent, if only the specific groups one identifies with matter. This may imply that the linear-in-mean peer effect models will not be useful as a guide at higher levels of group specification. Moreover, coupled with lessons from the identity literature on group identity effects, it may also indicate that random assignment into groups will fail to generate strong peer effects unless actual group identification forms between people in the group. This also makes it difficult to compare peer effect studies using salient group identification with the literature exploring peer effects at the dorm, class, or course level.

Group level peer effects, at say the classroom or course level, may mask the impact from a few individuals that a person bonds with. Future studies implementing random group assignment should consider whether sufficient conditions for group bonding are met. When they are not, little in the way of peer effects may be generated. This implication casts doubt on the usefulness of manipulating peer groups as a policy mechanism for improving outcomes, at least without first understanding how social links are formed and which social links actually matter. More research on these topics is needed to provide any policy relevant insights.

2.5 Final Remarks on the Literature

I have reviewed the literature in identity economics, skill development, and peer effects and drawn from them to motivate several research questions. Do family and peer effects form influences that can combine or compete? Do social group effects create lasting influences? And, if

so, what mechanisms can the current literature motivate as possible channels for lasting group influences? Finally, under what conditions are peer effects generated? I put forward as potential channels of lasting group influence the creation of beliefs, groups as inputs to skill development, and network resources. Moreover, the literature will benefit from exploring how these channels may dynamically interact. I also relate the lessons from the identity literature with the peer effects literature to discuss how peer effect studies using networks and those using group assignment at the dorm, classroom, or some other level relate. It is not clear at this time whether substantial peer effects are generated unless one identifies with the group. Further understanding of these points is needed for any relevant policy considerations.

The evidence in the literature does point toward social groups, especially for children and adolescents, as important contributors to life outcomes. Incentives can be monetary and social, where the social incentives stem from the most important groups in one's life. Social incentives develop as rational responses over multiple periods that can impact choices in ways that are seemingly irrational if we neglect the social component. Skill development, cognitive and noncognitive, during childhood and adolescence is highly important to later life outcomes. Families have been shown to have a role. Peers may too but we need to explore this question in more detail. The study of peer effects is broad, difficult, but making progress. Social behaviors tend to exhibit the strongest peer effects. And, the evidence suggests that groups one actually identifies with tend to generate strong effects. Bringing together insights from across these literatures is a step towards a more cohesive picture on the determinants of development and overall life outcomes.

This dissertation delves into the role of families and peers for schooling attitudes and performance among adolescents. Because non-cognitive skills are malleable these attitudes will be shapeable and affected by the development of these non-cognitive skills. To the extent that families and peers influence skill formation, the identity literature provides a framework to consider how such incentives are passed about and spread over school networks social link to social link. The remaining research gaps noted in this chapter motivate a research agenda beyond my empirical study.

CHAPTER III

A THEORY OF IDENTITY FOR CHOICE UNDER COMPETING INCENTIVES

In this chapter, I consider a theoretical model of conflict between personal identity and group identity and then build on that to model two group identity inputs that may combine or compete. The first is a model of social interaction where a concept of location in reference to one's group may impact choices through consumption of goods produced in the network and identity. The model is a generalized model that links to both the identity economics literature and the network economics literature investigating the role of peer effects and network structure on choices. The individual is motivated by social interaction corresponding to how close or far away they are from the group. Identity here is similar to the concept developed by Akerlof and Kranton in a series of papers showing how actions by the individual and those around them may affect the agent's sense of self and yield outcomes not apparent from traditional economic models lacking social preferences (Akerlof and Kranton 2000, 2002, 2005). I show that the consumption benefits from goods produced in the network and the identity effect can work together or in opposition. When they work together, the incentives to be close to one's group are strong, and when they are in opposition, the individual faces a trade-off between the consumption and identity utility. This result develops how a constraint can exist from the interplay between social groups, or networks, and personal tastes.

The second theoretical development builds on the potential personal/group identity conflict and considers a model of two group identity influences. This model is applied specifically to adolescents and focuses on family and peer effects for choice of effort in school. Furthermore, I draw from the skill development literature to include the role of a malleable trait, attitudes about school, on effort in school and for families and peers in producing it. The empirical analyses of this dissertation is focused on testing implications that are tied to the second theory development.

Overall, the theory in this chapter as a whole continues the goal, began in the previous chapter, of drawing from the identity, skill development, and network literature to motivate and explore new hypotheses and research questions.

Drawing from both the peer effects and identity theory literature, I assume as one draws closer to their group the pressure to conform to the prescribed actions for the individual's assigned social category become stronger. So, the individual who is closer to their group conforms their actions by these prescriptions or else loses their consumption benefit of goods produced in the network. Further, in the first model application I allow the individual to agree or disagree with those prescriptions. In cases where one disagrees, the trade-off is between a positive marginal utility of network consumption from moving closer to the group and the negative marginal identity utility as increasing closeness implies conformity to the prescribed actions. In the second model of two group influences, neither group must agree in the ideals transmitted.

The model suggests that even when an agent disagrees with the actions prescribed for them by their group they may still remain close to the group and follow the actions prescribed, when they would do otherwise absent their group. This result can lead to poor outcomes in situations where the group takes part in risky health behaviors, incentivizes low academic achievement, and the like. Agents derive strong benefits from their social group surroundings and when strong enough these benefits assimilate the individual to the behaviors consistent with the groups ideals. Moreover, this suggests interventions designed to reach a target audience may, at times, find willing receipts but for whom it is ineffective without taking the significant group in their life into consideration. Likewise, the two group identity model suggests that taking the important groups to an adolescent into account is important for any program aimed at motivating better attitudes and effort in school.

Although the model in this section is simple and very general it unveils a potential constraint between networks and identity. The scarce resource is both the benefits one gains from their peer groups, not available for purchase on a traditional market, and the production of one's

sense of self constrained by the interplay of personal characteristics and social assignments by the group surrounding the individual.

3.1 Base Model Introduction

The base model is simply $u_i = u_i(X_i, I_i)$ where the choice of closeness to the individual's social group g_i produces both inputs. Let identity be $I_i = I_i(g_i, \boldsymbol{\gamma}_i; \epsilon_{ip})$ and suppose g_i to be a loosely defined, continuous measure of closeness to one's group, $\boldsymbol{\gamma}_i$ is an individual specific vector of any parameters impacting identity payoffs and ϵ_{ip} represents whether an agent personally agrees or disagrees with the assignment of social category and prescription for actions from their social group. Let the network consumption good from interaction in the individual's group be $X_i = X_i(g_i, \boldsymbol{\gamma}_i)$. These goods could be simply the company of other people, ethnic language, the safety of community trust, and more. The following identifying assumptions are made on utility: $\frac{\partial u_i}{\partial X_i} > 0$, $\frac{\partial^2 u_i}{\partial X_i^2} < 0$, $\frac{\partial u_i}{\partial I_i} > 0$, $\frac{\partial^2 u_i}{\partial I_i^2} < 0$, which along with the continuity of g_i implies utility is a well behaved continuously differentiable function.

The interplay between personal preferences and social directions for action defined as

$$\epsilon_{ip} = \begin{cases} 0 & \text{if i disagrees with category assignment and prescriptions} \\ 1 & \text{if i agrees.} \end{cases}$$

Let $g_i \in [0, \bar{g}]$ be bounded from below by 0 and above by $\bar{g}$ such that 0 implies having left the group altogether and $\bar{g}$ being as close to one's group as possible. This insures solutions exist for all cases and is sensible since one cannot increase their physical or mental closeness to others without limit. The marginal impact of a change in g_i on X is assumed to always be positive with diminishing returns, so $\frac{\partial X_i}{\partial g_i} > 0$ and $\frac{\partial^2 X_i}{\partial g_i^2} < 0$. The further one moves away from the group, the less one is able to gain such benefits.

When $\epsilon_{ip} = 1$, then as agent i increases g_i I increases with diminishing returns so let $\left.\frac{\partial I_i}{\partial g_i}\right|_{\epsilon_{ip}=1} > 0$ and $\left.\frac{\partial^2 I_i}{\partial g_i^2}\right|_{\epsilon_{ip}=1} < 0$. When $\epsilon_{ip} = 0$, then as agent i increases g_i I decreases at

an increasing rate so let $\frac{\partial I_i}{\partial g_i}\Big|_{\epsilon_{ip}=0} < 0$ and $\frac{\partial^2 I_i}{\partial g_i^2}\Big|_{\epsilon_{ip}=0} < 0$. Agents who agree with their groups norms and assignment of actions gain identity utility by moving closer to the network in some space be it physical, time, or some other frame of reference up to some optimum. For agents who do not agree, then moving closer to the network in some space lowers their identity utility, while this agent still receives the increase in the consumption benefit X. Thus, they face a trade-off between I and X and their choice of g will depend on this relationship. Living apart from the network would allow achieving a strong sense of self through making actions consistent with their personal preferences available to them but would result in the loss of social consumption benefits, or social identity. This loss of X can be understood as simply the requirement of X to be produced by closeness or may be restated as a punishment inflicted from the members of $i's$ group as i lowers their conformity to the groups prescriptions. This brings up an important assumption for the model.

Assumption 3.1.1. Let an agent i be conforming to the group's specified actions as g_i increases for all ϵ_{ip}.

The implication from this assumption, is that conformity in actions for the individual has a positive linear relationship with closeness to the group. For the agent who disagrees, this implies closeness to the group places more pressure to conform else be pushed out and lose X, and for the agent who agrees, it implies being closer to a group who holds the same values makes it easier to continue in the actions they already desire to take. Potentially, for the one who agrees moving away from the network may place them around those with different values making it more difficult to continue in their desired actions and increase identity.

Assumption 1 may be a strong assumption. One could suppose that individuals need not necessarily conform as they move closer to their group. Given the literature discussed in chapter 2, I think assumption 1 is a reasonable assumption. When it does not hold then the agent does not interact with the constraints imposed by this model.

I lay out possible criticisms of assumption 1 from the network literature and provide answers from the same literature. Agents themselves will effect the prescriptions for action of the group, so there is a simultaneous system at play, not considered in the base model. Research in economic network theory by Ballester, Calvó–Armengol, and Zenou (2006) and Ballester and Calvó–Armengol (2010) has found measures of individual centrality within the network are important to the profile of Nash Equlibria (NE) in games of social interaction played on a network such that an agents NE is proportional to their Bonacich-Katz centrality.[1] Some agents may impact the prescriptions for action more than others so a conjecture is that as g_i increases the agent gains more ability to effect the groups ideals and that over time she may be able to move the group closer towards prescriptions for action aligned with her preferences. In such a case, the key assumption of this model may not hold, especially over time.

The results corresponding NE to Bonacich-Katz centrality break down in Belhaj, Bramoullé, and Deroïan (2014). They bound the action space from above in network games of complements arguing this is sensible to most situations. Now, the previous relationship does not always hold and the best response function becomes a censored best reply. A clear relationship between position and action is identified when the action space is bounded from above. When the agent has fewer neighbors included in their set, then they play a lower action than an agent with more. This fits well with the assumption of this paper. Furthermore, they find when an agent hits their upper bound they cease transmitting shocks across the networks breaking interdependence. Agents who are bridge agents between sets are especially important since once they hit their upper bound no further effects from increased action pass across the sets. These agents often reach the most central position the quickest and may be seen as hitting $\bar{g}$ in my model. So, indirect effects break down once one agent in the path hits their upper bound.

Those who hit the upper bound would not transmit indirect positive impacts to their links. However, this is not a difficulty for the assumption of this model. When the individual

1. Bonacich-Katz centrality is a measure of network centrality that considers both direct and indirect links. See Ballester, Calvó–Armengol, and Zenou (2006) and Ballester and Calvó–Armengol (2010) for more detail.

moves closer to the group, their conformity in action does not rely on shocks transmitted across the network. Shocks across the network are exogenous changes entering the comparative statics. Although this may create some difficulty in the comparative statics for changes in action of other group members. Agents who hold such a position may not effect other agents when a parameter is changed unless that parameter lowers their closeness. This is not considered in depth at this time.

Network structure may also matter to this assumption. Theoretical research shows that network structure is important to the existence of unique and stable NE. The network structure matters to how the cross effects of one agents actions on others is amplified throughout the network. Bramoullé, Kranton, and D'amours (2014) show this is important in games of substitutes and characterized by the lowest eigenvalue of the network. Ballester, Calvó–Armengol, and Zenou (2006) found convergence in the series of indirect effects of agents actions on others to a unique NE depends on the cross effects of actions being sufficiently small compared to the largest eigenvalue of the network matrix describing how network structure amplifies these cross effects. When the interaction effects are too large no equilibrium exists. Networks where amplification is very weak may break Assumption 1. Thus, my model may be sensitive to the individual's network centrality and network structure.

Bounding the action space from above, as is done is this model, may help solve the issues surrounding my main assumption and network amplification. Again, I turn to Belhaj, Bramoullé, and Deroïan (2014) for guidance. Their work shows that in games of complements bounding the action space from above yields existences of equilibrium for all linear and concave functions of peer effects, and that even under convex functions of peer effects unique NE can emerge if it is not too convex. In linear best replies, this implies the parameter describing cross effects need not be small for uniqueness to hold. This provides strong support for bounding the action space in this model as a precursor to linking the model to games on networks.

The structure of this model links games of peer effects with identity theory where the actions of others are contained in the vector γ_i and the combination of consumption and identity determinants may allow mixed games of complements and substitutes to arise which pull the agent

in different directions under certain conditions. Furthermore, it provides a ground level starting point to delve into the mechanism underlying why peers actions may enter an agents payoff structure rather than simply stating that they do and inserting them. This may be more important as an explaining mechanism in the context of peer effects in school or health than on public goods where one would only desire a certain optimal amount and need not put forth effort if their peers put forward effort in its provision. Restriction the choice variable g_i has both a sensible explanation and a natural counterpart in games of complements where restricting the strategy space is necessary to obtain results.[2]

The model serves first to motivate construction of hypotheses for empirical testing that can be applied to a broad range of questions related to social groups and individual choices. Additionally, the following results are a step towards explaining why some agents may move away from their network and a base to expand towards an explanation of how agents may be seduced out of their current group into other groups.

3.2 Solutions and Results

In the base model outlined above, no other constraint is needed other than that which arises from restricting g_i and between consumption and identity when the individual's personal preferences do not agree with their prescriptions from the social group. The individual optimization problem is simply given by

$$\max_{g_i} \quad u_i = u_i(X_i, I_i) \quad s.t. \quad 0 \leq g_i \leq \bar{g}$$

The lagrangian follows as

$$\mathcal{L} = u_i + \lambda_1(\bar{g} - g_i) + \lambda_2 g_i,$$

2. See Belhaj, Bramoullé, and Deroïan (2014) and Bramoullé and Kranton (2016) for further discussion on restricting the strategy space in games of complements.

and the first order conditions are

$$\mathcal{L}_{g_i} = \overset{(+)}{\frac{\partial u_i}{\partial X_i}} \overset{(+)}{\frac{\partial X_i}{\partial g_i}} + \overset{(+)}{\frac{\partial u_i}{\partial I_i}} \overset{(+/-)}{\frac{\partial I_i}{\partial g_i}} - \lambda_1 + \lambda_2 = 0$$

$$\mathcal{L}_{\lambda_1} = \bar{g} - g_i = 0; \qquad \lambda_1 \geq 0$$

$$\mathcal{L}_{\lambda_2} = g_i = 0; \qquad \lambda_2 \geq 0.$$

Again, the sign of $\frac{\partial I_i}{\partial g_i}$ depends on ϵ_{ip}.

Proposition 3.2.1. If $\epsilon_{ip} = 1$, then $g_i^* = \bar{g}$.

Proof. The proof is straightforward as u_i is increasing at a decreasing rate in g_i from both X_i and I_i. ■

In the absence of any other determinants to the utility function, this result is elementary. Incentives are clearly aligned for the agent to maintain strong links to their group. Any other element entering utility working opposite of social consumption and identity would have to compete strongly with X and I to move the agent away from their group.

The more interesting case is when personal preferences do not align with the prescriptions for action of the group. Now, $\epsilon_{ip} = 0$ and the agent will face a trade-off between social consumption and identity. Notice that $\frac{\partial I_i}{\partial g_i}$ is negative in this case. For ease of exposition, define MXUg as the marginal utility from X for a change in g ($\frac{\partial u_i}{\partial X_i} \frac{\partial X_i}{\partial g_i}$) and MIUg is the marginal utility from identity for a change in g ($\frac{\partial u_i}{\partial I_i} \frac{\partial I_i}{\partial g_i}$). I now show the conditions for corner and interior solutions.

Proposition 3.2.2. When $\epsilon_{ip} = 0$, lower and upper bound results occur when either MXUg or MIUg dominate the action space $g \; \forall \; g_i$ or in the special case that they are equal to each other at a bound (lower/upper) but the bound is non-binding. An interior solution occurs where the marginal utilities of X and I from a change in g_i are equalized, if and only if lower or upper bound results do not hold.

Proof. Consider first the following requirements from standard Kuhn-Tucker conditions:

$$\lambda_1(\bar{g} - g_i) = 0, \quad \lambda_2 g_i = 0.$$

(A) **Upper Bound Results**.

(i) *Social group benefits dominate*. Suppose $\lambda_1 > 0$ then $\bar{g} - g_i = 0$, which means $g^* = \bar{g}$ and $\lambda_2 = 0$. Thus, rearranging the first order condition from the lagrangian with respect to g_i we have $\lambda_1 = \overset{(+)}{MXUg} + \overset{(-)}{MIUg}$. Because $\lambda_1 > 0$, it must be that $|MXUg| > |MIUg|$. In this case, $MXUg$ dominates the action space $\forall\ g_i$. For any increase in $\bar{g}$, g_i^* would increase until $MXUg$ equaled $MIUg$.

(ii) *Special Case*. Suppose $\lambda_1 = 0$ and $\bar{g} - g_i = 0$ then $g^* = \bar{g}$ and $\lambda_2 = 0$. This implies that $MXUg = -MIUg$ precisely at the upper bound. In this case, the marginal utility of $\bar{g}$ (λ_1) is zero, thus an increase in $\bar{g}$ would not result in a change to g_i.

(B) **Lower Bound Results**.

(i) *Identity incentives dominate*. Suppose $\lambda_1 = 0$ and $\lambda_2 > 0$ then it must be that $g_i^* = 0$. Rearranging the first order condition for the lagrangian with respect to g_i we have $\lambda_2 = -\overset{(+)}{MXUg} - \overset{(-)}{MIUg}$. Because $\lambda_2 > 0$, it must be that $|MIUg| > |MXUg|$. In this case, $MIUg$ dominates the action space $\forall\ g_i$.

(ii) *Special Case*. Suppose $\lambda_2 = 0$ and $g_i^* = 0$ then we must have $\lambda_1 = 0$. This implies that $MXUg = -MIUg$ precisely at the lower bound.

(C) **Interior Solution**. Suppose $\lambda_1 = 0$ and $\lambda_0 = 0$ and $0 < g_i^* < \bar{g}$. In this case, for any g_i^* we have $MXUg = -MIUg$.

■

When one incentive dominates, the trade-off between social consumption goods and identity never equalizes inside the action space. The person is either willing to give up all the social

consumption from their group and become isolated or pay a high cost in terms of their personal identity. Of course, some people choose to maintain some closeness to their group that is less than the upper bound and greater than the lower bound if the benefits from the group equalize with identity costs within the action space.

Figure 1 provides graphical examples of the result for lower and upper bound solutions. The solid line at the lower and upper bounds illustrates the result when either MUXg $<$ MIUg or MUXg $>$MIUg for all g_i. Finally, the dashed lines correspond to MUXg $=$ MIUg at one of the extremes.

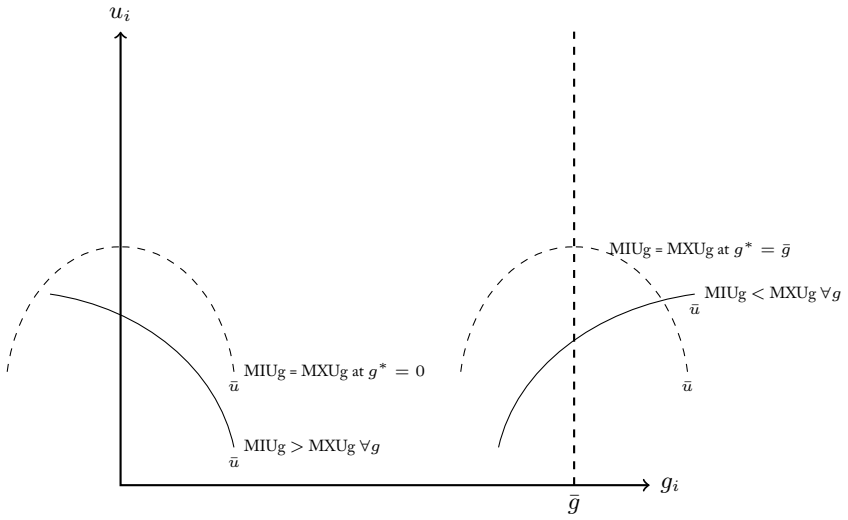

Figure 1. Lower and Upper Bound Solution Examples from Proposition 2 Results

Given an interior solution MXUg $=$ MIUg. Recall that this condition means the individual is engaged in a trade-off between social consumption and their loss of identity utility from coming closer to their social group to the point where the marginal gain in social consumption from g is equal to the marginal loss of identity from g. Figure 2 illustrates an interior optimum. The trade-off between social consumption and identity contains the constraint that pulls the choice of g_i away from the lower or upper bound. A change in a parameter that effects only one of

social consumption or identity shifts g_i^* by the impact of that parameter on the marginal utility of g_i.

The second order condition for an interior condition, and $\epsilon_{ip} = 0$, where I assume additive separability is[3]

$$\frac{\partial^2 u_i}{\partial g_i^2} = \overset{(-)}{\frac{\partial^2 u_i}{\partial X_i^2}} \overset{(+)}{\frac{\partial X_i}{\partial g_i}} \overset{(+)}{\frac{\partial X_i}{\partial g_i}} + \overset{(+)}{\frac{\partial u_i}{\partial X_i}} \overset{(-)}{\frac{\partial^2 X_i}{\partial g_i^2}} + \overset{(-)}{\frac{\partial^2 u_i}{\partial I_i^2}} \overset{(-)}{\frac{\partial I_i}{\partial g_i}} \overset{(-)}{\frac{\partial I_i}{\partial g_i}} + \overset{(+)}{\frac{\partial u_i}{\partial I_i}} \overset{(-)}{\frac{\partial^2 I_i}{\partial g_i^2}} < 0,$$

so the SOC for a maximum at MXUg = MIUg holds.

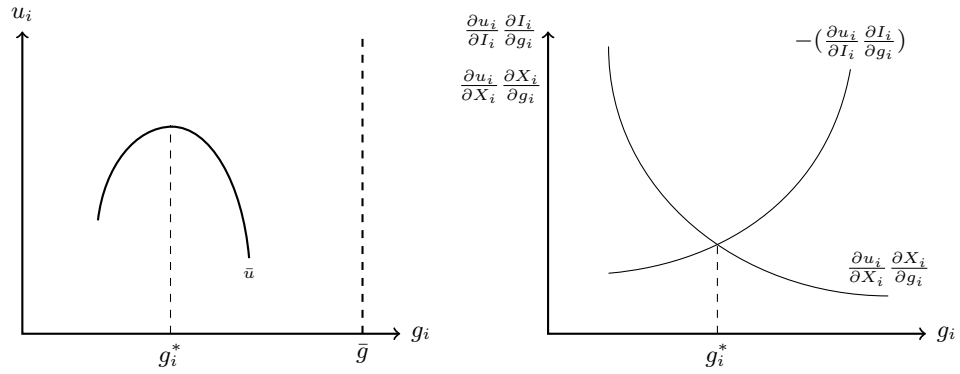

Figure 2. Illustration of Interior Optimum when $\epsilon_{ip} = 0$

Exploring how a parameter γ impacts both social consumption and identity will also uncover how a parameter impacting only social consumption or identity will work. Considering a change in a parameter γ four pathways emerge for which an increase in γ can work through social consumption and identity to move g_i^*. One, an increase in γ may increase the social consumption benefit of g_i. Two, it may increase identity cost from g_i. Three, it may decrease the social consumption benefit of g_i. Four, an increase in γ may decrease identity cost from g_i. When γ works through both social consumption and identity then two of these cases at a time combine to determine the movement of g_i^*. For example, if γ increases social benefit and increases identity cost from g_i then the agent gets more X_i for all g_i but greater identity cost for all g_i. Now, the move-

3. To simplify notation, for the remainder of this paper $\epsilon_{ip} = 0$ unless otherwise noted.

ment of g_i^* could be down or up contingent on the strengths of these two moving parts. Furthermore, if a parameter increases the amount of X_i available at all g_i then lowering g_i may allow gaining more identity utility back than social consumption lost until the marginals equal again. This process could work in reverse where a parameter making identity losses even more costly may yield an increase in g_i^* since now decrease g_i may not yield enough identity utility back to make up for the loss in social consumption. This would imply the agent falls to an overall lower utility point but the best they can do is increase g_i, suffer the increased loss in identity, and take the increased social consumption. The following explores these issues through comparative statics and the implicit function theorem.

For a parameter impacting both social consumption and identity, the change in the agent's optimal closeness for a change in γ is given by

$$\frac{\partial g_i^*}{\partial \gamma} = -\frac{\left[\frac{\partial^2 u_i}{\partial X_i^2}\frac{\partial X_i}{\partial \gamma}\frac{\partial X_i}{\partial g_i} + \frac{\partial u_i}{\partial X_i}\frac{\partial^2 X_i}{\partial g_i \partial \gamma} + \frac{\partial^2 u_i}{\partial I_i^2}\frac{\partial I_i}{\partial \gamma}\frac{\partial I_i}{\partial g_i} + \frac{\partial u_i}{\partial I_i}\frac{\partial^2 I_i}{\partial g_i \partial \gamma}\right]}{\frac{\partial^2 u_i}{\partial g_i^2}}. \tag{3.1}$$

The denominator is negative implying the sign of this derivative depends on the term inside the bracket of the numerator. Without knowing something about a functional form it may be hard to sign both the direct and indirect effects, $\frac{\partial X_i}{\partial \gamma}$ and $\frac{\partial^2 X_i}{\partial g_i \partial \gamma}$ for social consumption and $\frac{\partial I_i}{\partial \gamma}$ and $\frac{\partial^2 I_i}{\partial g_i \partial \gamma}$ for identity. However, for many examples that are sensible to this framework, such as the density of the group or educational programs building openness and changing prescribed actions within the group considering only the impact γ has on how g_i effects X_i and I_i is a reasonable assumption.

Assumption 3.2.1. Let $\frac{\partial X_i}{\partial \gamma} = 0$ and $\frac{\partial I_i}{\partial \gamma} = 0$ so that the effect from a change in γ works entirely through the impact of g_i on X_i and I_i.

Implementing this assumption equation 2.2 becomes

$$\frac{\partial g_i^*}{\partial \gamma} = -\frac{\left[\frac{\partial u_i}{\partial X_i}\frac{\partial^2 X_i}{\partial g_i \partial \gamma} + \frac{\partial u_i}{\partial I_i}\frac{\partial^2 I_i}{\partial g_i \partial \gamma}\right]}{\frac{\partial^2 u_i}{\partial g_i^2}}. \tag{3.2}$$

The following proposition explores four cases possible for the impact of a change in γ on g_i^*.

Proposition 3.2.3. Given assumption 2.1 and $\epsilon_{ip} = 0$ the following cases hold for a change in γ:

(i) if $\frac{\partial^2 X_i}{\partial g_i \partial \gamma} > 0$, and $\frac{\partial^2 I_i}{\partial g_i \partial \gamma} < 0$ then a change in g_i^* depends on whether social consumption or identity cost effects dominate,

(ii) if $\frac{\partial^2 X_i}{\partial g_i \partial \gamma} < 0$ and $\frac{\partial^2 I_i}{\partial g_i \partial \gamma} > 0$ then a change in g_i^* depends on whether social consumption or identity cost decrease more,

(iii) if $\frac{\partial^2 X_i}{\partial g_i \partial \gamma} > 0$ and $\frac{\partial^2 I_i}{\partial g_i \partial \gamma} > 0$, then g_i^* is always increasing as γ increases,

(iv) if $\frac{\partial^2 X_i}{\partial g_i \partial \gamma} < 0$ and $\frac{\partial^2 I_i}{\partial g_i \partial \gamma} < 0$, then g_i^* is always decreasing as γ increases.

Proof. Note, $\frac{\partial^2 I_i}{\partial g_i \partial \gamma} > 0$ implies as γ increases $\frac{\partial I_i}{\partial g_i}$ becomes less negative and $\frac{\partial^2 I_i}{\partial g_i \partial \gamma} < 0$ implies as γ increases $\frac{\partial I_i}{\partial g_i}$ becomes more negative. A simple look at equation 2.4 shows that for case (i) $\frac{\partial g_i^*}{\partial \gamma} > 0$ when $\left|\frac{\partial^2 X_i}{\partial g_i \partial \gamma}\right| > \left|\frac{\partial^2 I_i}{\partial g_i \partial \gamma}\right|$ and less than zero otherwise. For case (ii), $\frac{\partial g_i^*}{\partial \gamma} > 0$ results from $\left|\frac{\partial^2 X_i}{\partial g_i \partial \gamma}\right| < \left|\frac{\partial^2 I_i}{\partial g_i \partial \gamma}\right|$ and it is less than 0 otherwise.

Finally, case (iii) always yields a positive term inside the bracket of equation 2.4 which yields $\frac{\partial g_i^*}{\partial \gamma_i} > 0$. Similarly, case (iv) always yields a negative term for the numerator of 2.4 yielding $\frac{\partial g_i^*}{\partial \gamma_i} < 0$. ■

Figure 3, illustrates the results of proposition 2.2. At the optimal g_i, the slopes of the social consumption and identity functions must be equal. To illustrate this point, the negative of MIUg is taken to reflect the graph of MIUg across the g axis and g_i^* lies at the intersection. The movement of g_i^* as a parameter γ is changing depends on how γ effects the marginal utility of social consumption and the marginal identity cost from g_i. When the direction of the cross partials differ, then g_i^* can move in either direction. The consumption effect dominates when the impact of γ is stronger on how g_i effects X_i than it is for I_i, and the identity effect dominates when this relationship is reversed. This results in the movement of closeness following the sign of the dominate effect. For example, in case (i) if the identity effect dominates g_i^* falls despite more social

consumption being available at every g_i due to the increased costliness on identity outweighing the positive benefit. Next, cases (iii) and (iv) place strong incentives for the agent to move close to one of the action space extremes.

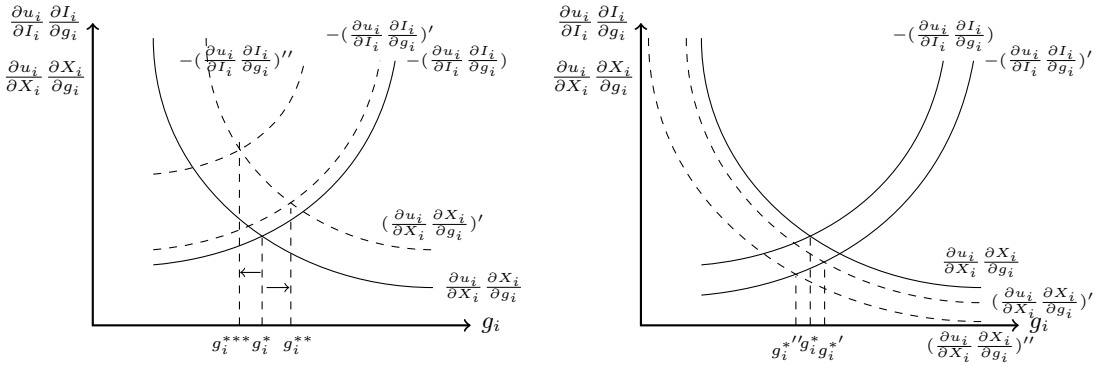

Figure 3. Illustrating Comparative Statics for Cases i and ii

Case (i) may be exemplified by the density of the social group. Suppose as the social group becomes more closely knit it provides more, or easier, access to the social consumption goods. However, it increases the identity cost for those with $\epsilon_{ip} = 0$ for all g_i through the effect of assumption 1.1 where closeness and conformity of action to the group's prescriptions are moving together. Now, the group can more effectively press for conformity to prescribed actions at lower levels of the individual's closeness.

An example of case (ii), requires some parameter that will both decrease the social consumption benefit and decrease the identity cost from moving closer to one's group. This could be something like a policy that disperses the group or makes it more difficult for the group to operate around its prescribed actions. The effect of dispersing the group would be to decrease the social consumption benefit and the identity cost for all g_i.

Case (iii) may be found through educational programs that impact the group towards more openness and less pressure for stringent prescribed actions. This, of course, would be tied to the actions of the other agents in the group taking part in the program and moving their own actions or characteristics. Also, this case could be the addition of new group members who share

notions of the prescribed action aligned closer to those with $\epsilon_{ip} = 0$. Though this example may require showing a change in the ideals of the group over time rather what is currently modeled.

Finally, case (iv) could be a change in the level of ridicule the group targets towards a member such that even when conforming an agent may find herself on the receiving end of ridicule. This results in the agent losing social consumption benefit for all g_i and an increase in the identity cost for all g_i.

Now, consider a simple extension of the model to evaluate how one's social group may impact an individual's production of, for instance, health or education. Introduce $f = f(g_i; \epsilon_i, \eta_i)$ where this could be consider either a health stock or years of education and it is conditional on personal characteristics and environmental factors surrounding the agent. A group may positively or negatively incentivize healthy or unhealthy behaviors and more or less educational attainment. This yields multiple cases for how the social group may impact these outcomes, but let us examine the case where the social group incentivizes poor health behaviors or poor educational outcomes. So, define $\frac{\partial u_i}{\partial f_i} > 0$ and $\frac{\partial f_i}{\partial g_i} < 0$.

The utility function is still a function of g_i where g_i works through X_i, I_i, and f_i. The first order condition for utility maximization is now

$$\frac{\partial u_i}{\partial g_i} = \frac{\partial u_i}{\partial X_i}\frac{\partial X_i}{\partial g_i} + \frac{\partial u_i}{\partial I_i}\frac{\partial I_i}{\partial g_i} + \frac{\partial u_i}{\partial f_i}\frac{\partial f_i}{\partial g_i} = 0.$$

Let $\frac{\partial u_i}{\partial f_i}\frac{\partial f_i}{\partial g_i}$ be called the marginal utility of f from g_i (MfUg). When $\epsilon_{ip} = 1$, an interior solution exists if $MXUg + MIUg = -MfUg$ for $0 < g_i < \bar{g}$. Upper and lower bound solutions can exist if $MXUg + MIUg \geq MfUg$ for $\bar{g}$ or $MXUg + MIUg \leq MfUg$ for $g = 0$. Clearly, the incentives are aligned for $g_i^* > 0$ when $\epsilon_{ip} = 1$. The case where an individual receives such negative cost through the f function from closeness to their group that they move away, despite positive impacts from social consumption and identity, could relate to groups engaged in very dangerous behaviors such that the individual becomes severely injured or addicted and ultimately decides the cost is to great. Of course, a more realistic framework may allow this great cost to change the agents identity

over time such that he no longer agrees with the groups actions giving him a further incentive to move towards $g_i = 0$. Clearly, the incentives are aligned for $g_i^* > 0$ when $\epsilon_{ip} = 1$.

When $\epsilon_{ip} = 0$, then an interior solution over $0 < g_i < \bar{g}$ is given by $MXUg = -MIUg - MfUg$. Social consumption benefits have to make up for the cost to the individual's identity and the cost working through f be it health behaviors or education. Upper and lower bound solutions again can exist with a similar logic to the case where $\epsilon_{ip} = 1$. The individual may desire to do well in school or to avoid an unhealthy behavior, such as poor diet, but find it difficult due to the influence of their group which is growing as they come closer to the group. In this case, strong social consumption benefits then make it difficult for the agent to move towards better education or better health behaviors.

Social groups promoting high education and healthy behaviors may have very positive effects on their members outcomes. So, the social group is not necessarily a bad in this model, rather this model shows how, at times, it can impact the agent and incentivize actions regardless of the individual's personal desires. Importantly, even when desiring to take a different action the agent may stay close and do otherwise in the presence of a social group providing positive social consumption benefits. A student may desire to study and pursue their education, but if their friend group(s) do otherwise, then benefits from having friends may outweigh their own identity and they may suffer poorer educational attainment than when alone. The implication for interventions is that it may find willing recipients to the course of action laid out by the intervention but a failure in results if that intervention cannot also offer valid social relationships yielding social consumption benefits.

3.3 A Network Model of Two Group Identities with Effort in School

I now extend and adjust the framework to consider the impact of two group identities on choice of academic effort. Explicitly the model is applied to adolescents and the family and peers are the groups of interest. In this extension, the potential conflict is not between individual tastes, or identity, rather potential conflict exists in the group ideals that can lead to differing outcomes.

Additionally, the focus is placed on adolescents in a school who have family and peers as their primary groups and who have malleable attitudes about school that are produced by family and peer ideals for education. It is to this model that the empirical analyses of this dissertation will be closely tied.

Family and peer identity influences are modeled as a framework of social inputs to adolescent academic effort. I draw from the theoretical work of Akerlof and Kranton (2000) and Akerlof and Kranton (2002) and shape it for two group inputs. Identity utility in their framework is produced as a function of one's own action's and the actions' of others conditional on ideals for action, social categories, and personal characteristics. For peers, once a person makes friends and enters a group, the ideal informs the person how to behave in the group.[4] Deviation from either family or peer ideals diminishes identity utility, providing an incentive to conform with the ideal for all group members.[5] Own-attitudes about school are added as a malleable trait that family and peer ideals shape and that impact performance in school. The model is framed in the context of a school where changes to ideals and attitudes can also create spill-over effects. Finally, the framework easily extends to a standard network theory model of social interaction.

An adolescent navigates their life choosing effort in school, influenced by the ideals on schooling transmitted to them from the family and the peer group. In this way, immediate returns to schooling are created through identity utility. Attitudes about school manifest a malleable trait that is shaped by an adolescent's surrounding environment. This includes the adolescent's primary social groups, which in this model are the families and peers.[6] Improved attitudes reduce the cost of effort for the adolescent, thereby improving effort. Thus, family and peer ideals may either influence the choice of effort through a conforming mechanism or indirectly through shaping attitudes. Additionally, the peer groups form a network structure across a school that allow changes in ideals or attitudes to send effects over the network handed across social link from social link.

4. I explicitly place the model post-peer group formation to focus on the affects of group ideals from family and peers.

5. For the purposes of this paper, ideals and norms are considered interchangeable. Another way to conceptualize ideals would be as aspirations.

6. The impact of teachers on attitudes may be an interesting extension, to apply with different data.

Adolescent social links in a school of n students are mapped in an $n \times n$ matrix $\mathbf{W}$. For adolescents *i* and *j*, the element $w_{ij} = 1$ if *i* is linked to *j* and is zero otherwise; $w_{ii} = 0$ to avoid self-links.[7] Assume there are no isolated individuals, to focus the study on network effects. An adolescent's total set of peers, is given by the row sum and denoted as $p_i = \sum_j = w_{ij}$.

Let the individual's own attitudes on school and academics be $a_i \in [0, 1]$. Tending towards zero represents negative attitudes about school, and tending towards one represents positive attitudes. For each *i*, average peer attitudes is given by $\bar{a}_i = \frac{1}{p_i} \sum_j w_{ij} a_j$.

Adolescent attitudes are produced by a function of family and peer ideals conditional on environments, or other factors, (b_i) given by $a_i = a_i(\alpha_{if}, \bar{a}_i; b_i)$. Following Akerlof and Kranton (2002) the prototypical behavior in the peer group proxies the group ideal. Attitudes about school are shaped in a production function but not chosen in my model. The family and peer inputs are assumed to have a positive relationship with attitudes. For the family, α_{if} is the transmission of ideals on education, and for the peers, prototypical attitudes in the group is represented by the average of peer attitudes.

The action space is $e_i \in [0, \hat{e})$, where e_i is the effort put forward in school bounded from above at $\hat{e}$.[8] Average peer effort is $\bar{e}_i$. The choice is academic effort, e_i, and the utility function is $U_i(e_i) = u_i(b_i e_i, SI_i)$. b_i capture all non-identity related inputs that affect the utility from effort. SI_i is the social identity function providing social identity utility.

The social identity function maps effort relative to the peer (p) group's ideal and the family (f) group's ideal. I assume the function to be additively separable in its components and draw insight from Akerlof and Kranton (2002) to express the social identity function as

$$SI_i = S_f - \frac{1}{2}\left(\frac{e_i}{3} - e(\alpha_{if})\right)^2 + S_p - \frac{1}{2}\left(\frac{e_i}{3} - \delta_p \frac{1}{p_i} \sum_{ij} w_{ij} e_j\right)^2 .$$

7. Symmetry is not imposed.

8. I bound the action space since effort in school feasibly has a natural upper bound, and this becomes an important topic for understanding social interaction effects on networks. See Belhaj, Bramoullé, and Deroïan (2014) for more on this topic.

Social identity utility from belonging to one's family is given by S_f and from the peer group is given by S_p. The cost to identity utility from deviating away from the ideals is captured by the squared difference of effort from each group ideal. In the family, $e(\alpha_{if})$ maps the family attitude about education as ideals for academic effort. In the peer group, the prototypical effort in the group proxies the ideal and is given by the average effort level in the peer group. The parameter δ_p is a peer group social interaction parameter that captures the conforming effect.

A straightforward implication from the social identity model of effort for two groups emerges. If the ideals between groups differ, then there are competing social incentives for choice of effort. When families and peers both transmit low educational ideals, then there are strong social incentives for low effort, and when both transmit high ideals, there are strong incentives for high effort. When the groups compete, the conflict creates incentives for a middling choice of effort unless one group dominates.

There is a cost from effort that is diminished or enhanced by an adolescent's attitudes. Let this be defined as $c_i = c_i(e_i, a_i)$, such that better attitudes about school lowers the psychic cost from effort.[9] In terms of a standard network model, I define the cost function to be $c_i = \frac{1}{6}e_i^2 - \gamma a_i e_i$, where $0 \leq \gamma \leq 1$ is parameter determining the strength of attitudes in diminishing the cost from effort.

Adolescents choses effort to maximize utility constrained by group ideals and the cost of effort. This occurs in the school network where all adolescents make their choice simultaneously. Allow utility to be additively separable in the inputs, which leads to a model much like the standard network model of peer effects. Each adolescent in the school network chooses effort by maximizing

$$u_i(b_i, \alpha_{if}, a_i, e_i, \boldsymbol{e}_{-i}|\boldsymbol{W}) = b_i e_i + SI_i - c_i(e_i, a_i).$$

9. A point consistent with the literature on noncognitive skill, which finds "psychic" costs explain underinvestment in education that may be determined by noncognitive skill development. See Heckman, Stixrud, and Urzua (2006) for notes from the literature and empirical evidence.

Solving the first order condition yields adolescent *i*'s best response function, $e_i = b_i + e(\alpha_{if}) + \delta_p \frac{1}{p_i} \sum_{ij} w_{ij} e_j + \gamma a_i(\alpha_{if}, \bar{a}_i; b_i)$. The best response function for effort is derived from the identity framework and depends on peer effort, family ideals, and an adolescent's own-attitudes produced by family ideals and peer attitudes. Families can impact the adolescent through both a conforming effect derived out of the social identity function and their influence on shaping own-attitudes. If δ_p is positive, then an adolescent positively responds to changes in the prototypical effort in the peer group. Also, peer attitudes can influence the choice of effort through shaping own-attitudes.

Belhaj, Bramoullé, and Deroïan (2014) formally establish that a profile of unique Nash Equilibria (NE) always hold for bounded games of complements with linear interaction effects.[10] Effort is defined with lower and upper bounds in the model—as it is reasonable that effort is not infinitely small or large. Thus, a profile of NE exists under the model conditions, and the vector of best responses is $\boldsymbol{e} = \boldsymbol{b} + \boldsymbol{\alpha}_f + \delta_p \mathbf{W}\boldsymbol{e} + \gamma \boldsymbol{a}$. Rearrange and solve for e_i to consider the effect of a change in peer effort, family ideals, or own-attitudes yielding:

$$\boldsymbol{e} = (\boldsymbol{I} - \delta_p \boldsymbol{W})^{-1}(\boldsymbol{b} + \boldsymbol{\alpha_f} + \gamma \boldsymbol{a}). \tag{3.3}$$

The series expansion of the inverse term is

$$(\boldsymbol{I} - \delta_p \mathbf{W})^{-1} = \sum_{k=0}^{\infty} (\delta_p \mathbf{W})^k = \mathbf{I} + \delta_p \mathbf{W} + \delta_p^2 \mathbf{W}^2 + ...,$$

where the powers of $\mathbf{W}$ return second order links and so on.[11] Thus, the inverse term accumulates the cross network effect from changes in effort, if $\delta_p > 0$. For example, an increase in own-attitudes improves effort. The improvement in effort spills-over to those linked in the network

10. They also show that unique equilibria can hold with large network effects even with convex interaction functions if they are not too convex. See Calvo–Armengol and Jackson (2009) for a study that does not require a bounded action space and relates NE in peer effects to Bonacich-Katz centrality.

11. A typical requirement for convergence has been $\delta_p \lambda_{max}(\boldsymbol{W}) < 1$, where $\lambda_{max}(\boldsymbol{W})$ is the largest eigenvalue of $\boldsymbol{W}$ (Ballester, Calvó–Armengol, and Zenou 2006; Ballester and Calvó–Armengol 2010). However, Belhaj, Bramoullé, and Deroïan (2014) show that with restricted action spaces convergence is achieved for all social interaction parameters.

through the simultaneity in the best response function, creating social multipliers captured by the inverse term in 2.1.[12]

Increases in family ideals improve attitudes. Improvements in attitudes for the adolescent implies an increase in the average peer attitudes for those linked to the adolescent. Thus, spill-overs in attitudes from changes in family ideals are present. While I have not assumed a functional form for the production of attitudes, in the empirics I will consider own-attitudes to be produced with a similar network effect. This leads to an implicit assumption that own-attitudes are produced by $\boldsymbol{a} = (\boldsymbol{I} - \theta_p \mathbf{W})^{-1}(\boldsymbol{b} + \boldsymbol{\alpha}_f)$, where θ_p is the network effect from average peer attitudes. In this framework, spill-overs in attitudes across the school network from changes in family ideals (α_{if}) will occur if $\theta_p > 0$.

The network effects spread influence from changes in family ideals or own-attitudes out through the network. Spill-overs from attitudes across a school lead to positive impacts on effort in school, if γ is not equal to zero. Families work through two channels, the conforming effect and their influence on shaping own-attitudes. Shifts in attitudes among adolescents in school and among families can work together to create large effects across a school if the social interaction parameters are greater than zero. I now introduce the data and an empirical model with spatial econometrics to tie into the theoretical framework.

3.4 Theory Application Examples

The theory laid out in this chapter relates to the identity economics literature and links to network theory and skill development. The results here fit nicely with the oppositional identity literature of Battu, Mwale, and Zenou (2007), Bisin et al. (2011b), and Hanming and Loury (2005) because by allowing the group to be a general notion of who the individual has links with allows those groups to have formed the oppositional identities or not found in these papers. In the case, of a group which has developed such oppositional identities among its members, then this theory

12. If bridging agents who have reached their upper (lower) bound exist between sets of adolescents, then positive (negative) shocks would be blocked from passing between the sets by these agents (Belhaj, Bramoullé, and Deroïan 2014). Also, see Bramoullé and Kranton (2016) for more details regarding games of complements played on networks.

relates to how strongly that oppositional identity will be for the individual with respect to how close they are to the group.

Immigrants and the children of immigrants form an interesting application. A great deal of work in the social sciences has concerned itself with how they assimilate and whether to whom they assimilate matters for their long run outcomes. Portes and Zhou (1993) proposed today's immigrant communities assimilate in a segmented matter, implying the path of assimilation is not always upwards towards the middle class but for some may be downwards. They suggest the communities and conditions surrounding immigrants greatly impact their opportunities for assimilation and often their outcomes. So, the immigrant family arriving with little money and forced into inner city areas underserved by public goods and prone to greater levels of violent crime may find their children assimilating to underclass groups. These groups, through discrimination and lack of opportunity, may not believe education is for them and may incentivize their members towards poor educational outcomes and other negative results. Rumbaut (1994) and Zhou (1997) review the experiences of the children of immigrants and provide more evidence and insights on how varying types of assimilation paths can yield poor results for these new Americans.

Segmented assimilation theory found in the sociological literature fits the economic theory developed here. Although, this theory does not attempt to explain group formation it does show the strength of the group one comes to belong to can have effects on the individual's decision making. When the only viable groups the children of immigrants find to assimilate to are those experiencing very negative education and health behavior outcomes themselves, then the ability to obtain social consumption may outweigh these costs and move these children towards outcomes their migrating parents had hoped to avoid. In this case, the family group and the peer group may impose competing ideals for behavior.

Suárez-Orozco and Suárez-Orozco (2001) in a substantive review of social science research pertaining to the children of immigrants find that parents immigrate with goals of achieving positive outcomes for their children. Indeed immigrant parents often work multiple, low paying jobs in hopes of achieving better results for their children. However, they also find parents

unable to guide their children away from negative assimilation paths can find their children struggling. Immigrant parents often lack a firm grasp of the surrounding culture and their reference points for socially guiding their children are gone. Additionally, extensive work time increases the difficulty in observing who their children's peer groups have become.

As immigrant parents time available to their children falls, the identity costs of moving closer to a group with a very different set of prescribe actions from the parents is falling. Combining the implications from the base model and the two group model suggests that as the costs of deviating from the family group ideals is falling then the peer group can dominate. When one group dominates, they essentially become the primary source of social incentives. This result shifts the children's optimal closeness to their peer group towards the upper bound in the base model. Also, the parents are now less able to place barriers on the social consumption goods their children are consuming. The parents may directly effect the level of g_i their children are allowed setting up barriers that prevent them from coming too close to a group incentivizing poor outcomes, thus they may be able to effect $\bar{g}$. Inability to set such barriers in the new context of a new culture and difficult surroundings may allow the children to move to the fringes of their parental home group and be pulled towards the prescribed actions of their peers.

Density of the ethnic home group (possibly larger family group) is another parameter that may enter the model here and one that can help the parents shift their children away from negative assimilation outcomes. Portes, Fernandez-Kelly, and Haller (2005) find empirical and ethnographic support for the theory of segmented assimilation, and also find that children of immigrants with strong family and community ties are more likely to follow less negative assimilation paths and achieve better long run outcomes. This may imply the ethnic community can help the parents in moving the parameters of the model in directions preventing the children from drawing too close to a group with poor education and risky behaviors. The authors note that community social capital depends more on the density of communal ties than on economic outcomes. The density of the child's home, ethnic group then enters as a parameter of my base model that when increasing may help prevent negative peer group outcomes.

The theory in this paper illustrates one potential path that the density of a child's ethnic, home group may have in a positive way. However, it is not the only path it may work through. Cutler, Glaeser, and Vigdor (2008) find ethnic segregation, which would go hand in hand with increasing ethnic density, may have short run positive benefits but can yield lower economic assimilation through lower social network connections with the broader society, leading to less opportunities outside the ethnic network. So, the density of the child's ethnic group could have contrasting results that are not entirely clear or reconciled from the current literature.

The news for immigrants in the US is not all bad news. In general, low skill immigrants to the US, even recent immigrants, have closed economic gaps, making up ground where other low skills groups have not. The economics literature offers some evidence that the second generation closes education gaps even when they are from low skill immigrant sub-sets (Card 2005; Chiswick and DebBurman 2004). Further, Smith (2015) indicates that Latinos in the US have achieved greater advances in education across generations than accomplished by European or Asian migrants. The mechanism driving upward progress for the children of immigrants is not well explained. Given the finding in the sociological literature that immigrant parents exhibit strong upward mobility expectations, a transmission of high educational ideals from immmigrant families to their children may have a role. In my model, immigrant families would transmit high ideals for education that press effort in school higher and build positive attitudes about school.

Finally, take the story told by Suárez-Orozco and Suárez-Orozco (2001) of a Gahnaian taxi driver in New York City with sons at Brown and Duke and with a third son he hoped would go to Harvard. Though his story is anecdotal, it is extraordinary. One of the primary factors he spoke of in guiding his children was a decision to carefully guard who they were friends with and to not allow them to work so he knew what influences were around them. In the model here and assuming the children initially desire to follow the families prescriptions, the father's actions would enter as a parameter of the model that decreases the social consumption benefit from moving closer to a group incentivizing risky behaviors and educational outcomes. Additionally, it may also direct the children towards a set of social groups yielding better outcomes. In this case, his actions

would increase the identity benefit from drawing closer with a group prescribing high educational attainment.

3.5 Summary and Theory Conclusion

The economic theory in this chapter endeavors to unveil the degree of struggle that can arise between one's identity and their social groups and the role of multiple group identities for adolescent effort in school. In my model, the individual can do this through giving up the social benefit and moving away from their group. However, this may be difficult as illustrated. This chapter also extends to consider the potential for two competing group identities in the specific context of an adolescent choosing effort in school. Those groups are the family and peers.

This model incorporates both elements of peer effects and games of substitutes. As other agents decrease their set of actions that are opposing to the individual's personal ideals, then the individual may have an incentive to move closer to their group. This point, to my knowledge, has not been discussed in the literature.

The strength of peer effects may also be determined by the degree of identification with the group (Gioia 2017). In my model, this is captured agreeing with the group ideals and moving closer to the group. Thus, the peer group to test in an identity model is the group an individual identfies with. However, my model also predicts that a group whom an individual does not identify with may still have effects if those groups provide a sufficient amount of social benefits.

An alternative to groups representing an identity, is that individuals attempt to select from a menu of identities and match those with their group, as far as they can choose their group. In this case, their may be exogneously determined groups, such as family groups, and endogenously selected groups. Families still exert influence through incentives to conform. For friend groups peer influence heightens pursuit of the ideals in the identity by providing a collection of observable behaviors as a reminder of the ideals needed to exemplify the desired identity. In a sense, one attempts to select from a menu of identities and the presence of peers enhances the desire to display conformity with the chosen identity so that one will be seen as exemplifying the ideals and held in

high esteem by those who share the identity. Thus, the peer effect will still be rooted in an identity process. Of course, an adolescents may select friends based on other shared interests, while each adolescent is still in the process of selecting from a menu of identities. Once the adolescent makes friends the collective selection of identity in the group provides an incentive to match up to the ideals displayed in the group. Thus, again the presence of peer effects would be rooted in an identity mechanism that remains even after accounting for peer selection.

Families and peers in light of an identity mechanism create conforming incentives and produce attitudes about school that affect effort in school. The remainder of this dissertation empirically examines the theoretical results of this chapter applied to adolescents with family and peer influences.

CHAPTER IV
DATA AND METHODS

This chapter introduces the data for the dissertation study and the spatial econometric method used to examine research questions around family and peer influence on schooling attitudes and performance. Additionally, I discuss identification of key parameters.

4.1 Data

The National Longitudinal Study of Adolescent to Adult Health (Add Health) was selected for this study because of its in-depth data on adolescents, friend groups, and social context and life information. The data collection design selected a nationally representative sample of high schools, with over 90,000 students initially interviewed. The in-school survey allowed respondents to nominate their 10 closest friends. Respondents can be linked to the nominator, providing detailed information on the respondents' peer group. A subset of this sample consisting of just over 20,000 respondents was chosen for a more detailed survey to be conducted in the home. The in-home survey contains greater detail on the respondents' home and neighborhood. For the in-home survey, however, not all of the respondents' friendship nominations are included in the survey. Thus, one cannot construct the entire school peer network and include variables from the in-home survey.

Add Health provides a saturated sample of sixteen schools, where all students in the school were selected for the in-home interview. Of these schools, two were large schools with one mostly white and in a mid-sized town, and the other ethnically diverse and in a major metropolitan area. The remaining schools were scattered between rural and urban areas, some public and some private. The saturated sample provides friendship nominations for the 1994-95 school year from the in-school survey. A number of the respondents cannot be correctly linked between the in-school

and in-home survey because of missing data in the peer nominations. Add Health re-collected the school friendship nominations for the saturated schools in May of 1995, which re-gains many of the lost observations and places these friendship nominations closer to the actual dates of the in-home survey (occurred from May 1995–December 1995).[1] I select this sample, with the May friendship nominations, to explore the impacts of both families and peers on schooling attitudes and performance through the channels of social identity.

The survey design follows the in-home group through 4 waves of data collection, placing them close to 30 years old at the time of wave 4. Waves 1 and 2 are considered the adolescent period with wave 3 beginning the respondents' adult period. Those only in the in-school data are not followed through subsequent waves. Wave 1 is currently the only wave in use because of the need to include peer group information. However, I am using these later waves in post-dissertation projects. Add Health also provides contextual data for the in-home sample created from the 1990 census and other sources. This contextual data covers neighborhood and community information at the tract, block, and county level.

I focus on combined family and peer group influence on schooling attitudes and performance and draw on multiple measures, described below, to proxy these variables. To empircally test this combined influence, I use spatial econometrics. After discussion of variable selection and creation, I turn to presenting the method and discussion of identification challenges.

4.1.1 Variable Selection and Creation

Drawing from Add Health's in-home wave 1 survey, self-reported GPA is used as a proxy for academic performance. Each respondent is asked to list their grade on Mathematics, Science, English/Language Arts, and History/Social Studies over A,B,C, and D or lower. Reported letter grades are assigned values of 4 to A, 3 to B, 2 to C, and 1 to D and take an average that is the average of the non-missing responses to each course grade question.

1. All questions in the home survey related to schooling or other activities refer the respondent to answer for the 1994-1995 school year explicitly.

Own-attitudes about school is constructed as an index normalized to mean zero and a standard deviation of one using factor analysis. A set of scale-type questions related to how much a respondent reports a desire to go to college, how likely they think it is they will go to college, whether they feel apart of their current school, are happy at their current school, feel that their teachers are fair, and feel close to people at their school forms the index. Tables 1 and 2 contain summary statistics and information on the factor analysis. The factor analysis is conducted on the full sample post-listwise deletion of missing observations in the variables included for the factor analysis ($N = 3596$). Table 1 shows that all of the variables range from one to five. The scales are coded such that ones relate to the lowest report for a variable and fives the highest. Table 2 shows that all variables load strongly onto a single factor and only one factor in the analysis has an eigenvalue greater than one—the common cut-off rule for considering a factor as potentially relevant. Additionally, table 2 reports the factor scores used to generate an index out of these variables. For this disseration, I focus only on the composite variable generated from the factor analysis on these measures.[2]

Table 1. Summary Statistics for Variables Used in Factor Analysis

	Mean	SD	Min	Max	N
How Likely Variables					
Desire for College	4.30	1.12	1	5	3596
How Likely College	4.01	1.22	1	5	3596
Agree/Disagree					
Feel Part of School	3.81	1.04	1	5	3596
Happy to be at School	3.71	1.09	1	5	3596
Feel Teachers are Fair	3.52	1.05	1	5	3596
Feel Close to People at School	3.73	1.00	1	5	3596

2. Separating the measures into different components could be interesting but it is not clear why to do so and the factor analysis only generates a single factor with an eigenvalue above one.

Table 2. Factor Analysis: Factor Loadings and Eigenvalues

	Factor Loadings	Uniqueness
How Likely Variables		
Desire for College	0.532	0.717
How Likely College	0.537	0.712
Agree/Disagree		
Feel Part of School	0.681	0.537
Happy to be at School	0.616	0.621
Feel Teachers are Fair	0.356	0.873
Feel Close to People at School	0.579	0.665
Factor Eigenvalue	1.88	

The family ideal on education—α_{if} in chapter 3.3—is operationalized from respondents' perceptions of expected parental disappointment if failing to graduate college. A key assumption behind selecting perception of college disappointment is that these perceptions relate to the transmission of an ideal on academics from the parents to the respondent. Two college disappointment questions were asked, one for the mother and one for the father. These are Likert scale variables where 1 is low and 5 is high disappointment. I seperate the mother and father college disappointment variables into three variables apiece. Answers of 3 form a middle category representing a reference group to low and high responses. Answers of 1 and 2 are collapsed into a binary variable representing a low disappointment category and answers of 4 and 5 into a high category. I form a series of indicators combining the mother and father college disappointment reports. These are as follows: an indicator if two parents are in the low category (0 if a single parent home), an indicator if only one parent is in the low category (includes single parent homes), a reference category indicator if both parents are in the middle category (or if a single parent home is in the middle category), an indicator if only one parent is in the high category (including single parent homes), and an indicator if both parents are in the high category (0 if a single parent home).

The remainder of the variables cover controls for characteristics and environments that may influence the outcomes. Controlling for characteristics such as gender, ethnicity, parental education (which may proxy socio-economic status or simply the information available to the adolescent on the returns to education), language, and grade level in school (which may also capture maturity effects) are included in the list of covariates to control for homophily in peer group selection (M. O. Jackson 2011). Parental education, in this study, refers to the highest level of parental education in the household. Test scores from the Add Health Peabody Picture Vocabulary test, normalized to mean zero and a standard deviation of one, are included as a proxy for ability, because ability may lead to selection of peers with similar abilities. The adolescent's perception of other students' prejudice is used to proxy for possible discrimination that may raise a barrier and create negative schooling attitudes. The number of siblings in the home is included to capture more information about the family background that may be unrelated to identity, along with an indicator for single parent homes. Finally, indicators for language spoken in the home are included to control for peer group selection—if adolescents select peers based on language—and to capture potential language barrier effects that may influence outcomes.[3]

The Add Health data offers a variety of alternative variables that I do not utilize in this study. Before moving on, I will briefly describe one component of the data that may help dig into the black box of school fixed effects: the school administrative survey. Akerlof and Kranton (2002) theoretically describe how school policy can sort students into groups with differing ideals for effort. Their primary prediction is that a singluar school identity creates stronger incentives for effort in the group adopting the school identity compared to a school that supports a multiplicity of group identities; however, the singluar school identity sorts a higher share of students into groups that do not adopt the school identity and incentivizes low effort compared to the multiplicity approach. The attitude variables discussed above which specifically relate to how an adolescent feel's about their school can form measures of identification with one's school. Based on the theory I

3. Language spoken in the home is the best proxy I have found in the Add Health data for the ability to speak a language other than English.

expect some school policies may increase the attitudes of adolescent's in one group and decrease them in another. It also may influence the share of students in these different groups. The challenges to any analysis investigating this will be to identify pertient school policies, identify salient groups, and to identify the effect of school policies interacted with group membership sorting out bias from selection and other omitted variables. Therefore, I do not pursue this analysis here.

The school administrator questionnaire for the first wave of the data was conducted by phone with school administrators. It contains basic descriptions of the school type, demographics in the school (students and teachers), specializations, school performance, school programs related to sexual health, violence, drugs, alcohol, and smoking, policies for suspension based on misbehavior, and policies on hall pass requirements, dress codes, and student parking. The advantage of Add Health is that it provides this data for a nationally representative sample of adolescents along with a plethora of measures.

An example of one path forward would be to use the presence of a dress code or not and examine how this influences the attitudes of adolescents along racial and ethnic lines. In the presence of oppositional identities for any one group, a dress code may generate worse ties for the oppositional group, while it may generate stronger ties for groups whose norms match the code. Alternatively, a dress code in the school could foster a school identity that moderates ethnic divisions by providing students with something in common—if only something to complain about together. I leave further consideration to future work, but this discussion accomplishes two things: one, it suggests there may be heterogeneity in group effects on attitudes in school. The average spillover effects from peers that I will explore in this study do not allow for heterogeneous effects. In this dissertation, I seek to first establish whether these spillovers exist in networks. Two, it lays the groudwork for extensions to my dissertation that build on the identity model and attitudes about school. For this study, I will wash out specific influences from differing school policies through the inclusion of school fixed effects.

4.1.2 Mapping School Networks from Friendship Nominations

Add Health asked respondents for up to ten friendship nominations from which the school peer networks can be constructed as a spatial weights adjacency matrix (**W**). I use friendship nominations to define the links in the matrix. The spatial weights matrix is defined as a block-diagonal row-normalized directed graph. I call this **W** but note that it is a block-diagonal version of the network in the theory (chapter 3.3), which was developed for a single school. Each school network enters on the diagonal with zeros elsewhere. Some respondents have all friendship nomination slots missing. I drop these observations to avoid row entries that contain all zeros in the spatial weights matrix. In the directed graph, some respondents named only these dropped adolescents as peers and are subsequently lost. In the final sample construction, each individual has sent at least one link and receives at least one, and the sample size is 2,174 observations.[4]

Later, as a sensitivity test I consider an assumption of friendship reciprocity in the definition of the weights matrix to regain some of the lost observations. This leads to the undirected graph and means that the weight matrix maps social links such that anyone who was named by a schoolmate receives a link to that person regardless of whether they nominated them or not. In this case, the sample size rises to $2,725$. The caveat is that the reciprocity assumption may induce links where they do not exist.[5]

Figure 4 maps the nodes and edges for one of the Add Health Schools in the saturated sample. It illustrates that after removal of adolescents with all missing nomination slots, all members have at least one link. Also, the graph is directed denoted by the arrow, which signals that a node has nominated the other as a friend.

Figure 4 visually shows that each adolescent has direct and indirect links. Combined all of the nodes and edges form a graph and a network structure based on the nominations data for each

4. When deleting observations with missing friendship nominations, one school is lost leaving 15 schools total.

5. Lin (2010) and Lin (2015) have tested many iterations and different specifications of the weights matrix. Reassessing all of these iterations is not the focus of this paper.

adolescent. The matrix $\mathbf{W}_s$ maps each of these links for each node into a square matrix where each school enters on the diagonal with zeros elsewhere.

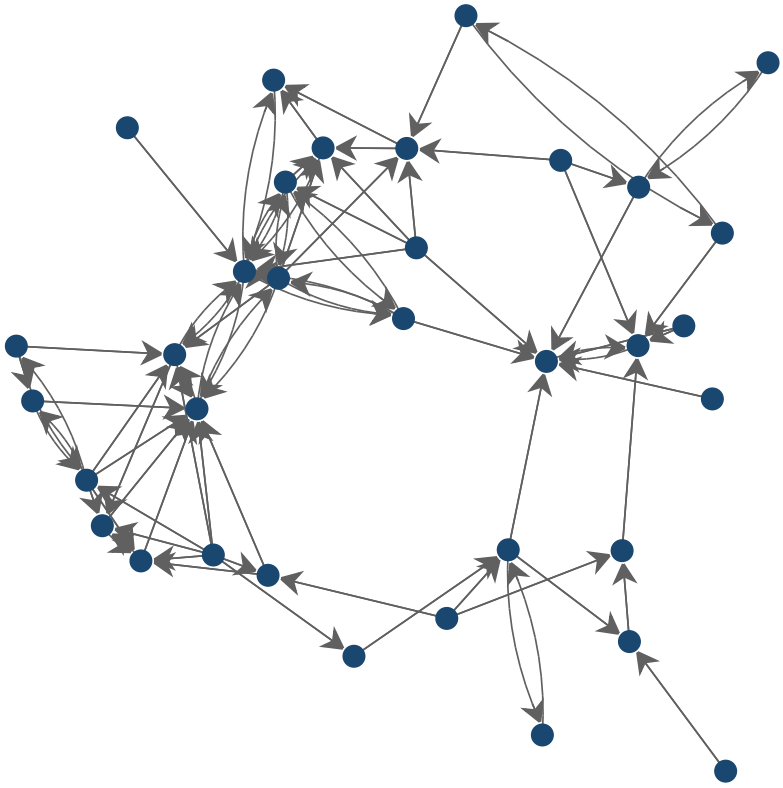

Figure 4. Graph of Directed Network Links for a Small Add Health School: An Example of Network Topology

4.1.3 Summary Statistics

Table 3 shows the summary statistics for the variables with the initial sample, after deletion of missing data, and the analysis sample after construction of the directed graph spatial weights matrix. For the majority of variables, the summary statistics remain consistent across the samples. However, average GPA rises from about 2.70 points to 2.75 points and the normalized factor analysis index, attitudes, climbs from approximately mean zero in the initial sample to a mean of 0.084 after deletion of islands for the directed graph. Additionally, the average score for the normalized

vocabulary test rises to 0.136. This appears to indicate that the islands deleted from the sample with the directed graph construction have lower attitudes and lower verbal reasoning skills. Demographically, the only compositional change by race/ethnicity is for blacks, with their share of the sample falling from about 15 percent to about 12 percent.

This study is focused on families plus network effects from in-school chosen peers. In that regard, we can consider the results conditional on being linked within the larger school network. As a very basic check, I explored a regression for the GPA model with own-attitudes, the family ideal indicators, and the controls as regressors—but no peer variables—with the sample post-listwise deletion of missing observations and the sample post-construction of the directed graph. Comparing the coefficient estimate for own-attitudes between the two samples yields a very similar result. Finally, as a sensitivity test I study the spatial models with the undirected graph, which imposes the friendship reciprocity assumption and returns many of the lost observations. Even in this sample, however, the attitudes index and vocabulary test scores in the the sample have means that are closer to the original sample but are still higher. Thus, the focus of this study is on those linked within the larger school network.

Again, the family ideal indicators are the indicators of adolescent perception for parental disappointment if they do not attend college. Two parents in the high disappointment category contains the largest share of the sample followed by the one parent high category. Combined, approximately 71 percent of all sample respondents report a minimum of 1 parent in the high category. The middle category will be the reference category and accounts for about 13 percent of the sample.

The controls section in 3 covers variables to control for background characteristics and peer group selection. The adolescent's perception of other students' prejudice is reported on a one to five scale with higher values indicating higher perceived prejudiced from other students. The mean is stable across the different samples. The highest education level of the parents remains stable over the samples at around 13.6 years of education. Single parent home account for about a

quarter of the sample and the number of siblings in the home averages about 1.5 across the subsets of the data.

Table 3. Summary Statistics

	Pre-Deletion of Missing		Post-Deletion of Missing		Sample with Directed W		Sample with Undirected W	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Self-Reported GPA	2.699	0.788	2.713	0.790	2.749	0.785	2.736	0.786
Attitudes	0.000	0.875	0.016	0.861	0.084	0.833	0.060	0.841
Parental Attitudes about College								
Two Parents in Low Category	0.082	0.274	0.079	0.269	0.074	0.262	0.075	0.264
One Parent in Low Category	0.112	0.316	0.111	0.314	0.102	0.303	0.104	0.305
Both Parents, or 1 Par H.H., in Middle C.D.	0.129	0.335	0.130	0.336	0.126	0.331	0.125	0.331
One Parent in High Category	0.290	0.454	0.285	0.452	0.282	0.450	0.279	0.449
Two Parents in High Category	0.416	0.493	0.423	0.494	0.444	0.497	0.442	0.497
Controls								
Picture Vocabulary Test Scores	-0.000	1.000	0.037	0.969	0.136	0.939	0.082	0.940
Feel Other Students are Prejudiced	3.148	1.231	3.168	1.237	3.217	1.227	3.188	1.226
Highest Parental Education	13.530	2.756	13.562	2.736	13.666	2.724	13.601	2.738
Single Parent Household	0.275	0.447	0.274	0.446	0.259	0.438	0.264	0.441
Number of Siblings	1.479	1.227	1.494	1.205	1.515	1.187	1.491	1.187
Female	0.489	0.500	0.497	0.500	0.492	0.500	0.501	0.500
Hispanic	0.204	0.403	0.196	0.397	0.183	0.387	0.194	0.395
Asian	0.147	0.354	0.140	0.347	0.155	0.362	0.145	0.352
Black	0.151	0.358	0.151	0.358	0.117	0.322	0.138	0.345
White	0.485	0.500	0.501	0.500	0.532	0.499	0.512	0.500
English Spoken in Home	0.848	0.359	0.855	0.352	0.853	0.354	0.852	0.355
Spanish Spoken in Home	0.102	0.303	0.098	0.298	0.097	0.296	0.102	0.302
Other Language Spoken in Home	0.051	0.219	0.047	0.211	0.050	0.218	0.046	0.210
School Grade	10.182	1.497	10.158	1.486	10.176	1.436	10.173	1.471
Observations	3702		3179		2174		2725	

Half of the sample is female and this does not change from the initial sample. Ethnicity/race indicators for Hispanic, Asian, black, and white are included with white used as the reference group in the analysis. Close to half the sample is white, with Hispanics composing an approximately 18 percent share, Asians close to a 15 percent share, and blacks around 12 percent. These values also stay consistent over the samples, excepts for blacks as noted previously. All indicators for language spoken in the home stay consistent over the samples and the same is true for the average school grade level.

4.2 Method: Spatial Econometrics

Empirically, I test both a model with own-attitudes as the dependent variable with peer attitudes, expected family disappointment if failing to graduate college, and controls, and a model with GPA—as a proxy for effort—as the dependent variable with peer GPA, own-attitudes, family disappointment, and controls as covariates. Interpretation of parameter estimates, especially for spill-over effects, does not rely solely on the coefficient estimates. These estimates do not take into account the endogenous effect—the simultaneously determined interaction effect from the peer average of the dependent variable—and therefore do not fully capture effects from a change in a variable. Investigating the implications from the theory, requires exploring both the endogenous effect estimates and then the partial effects that give estimates of direct, indirect (spatial spill-overs) and total effects from changes in an independent variable.

4.2.1 Empirical Model

For either own-attitudes or GPA as the dependent variable, the model can be expressed in a general spatial econometric form. Borrowing some notation from Lee, Liu, and Lin (2010) the generalized nesting spatial (GNS) model is given by

$$\mathbf{Y} = \mathbf{l}\kappa_s + \lambda\mathbf{W}\mathbf{Y} + \mathbf{X}\beta + \mathbf{W}\mathbf{X}\phi + \mathbf{u}, \tag{4.1}$$

where spatial autocorrelation in the error is captured by $\mathbf{u}_s = \rho_0\mathbf{W}_s\mathbf{u}_s + \epsilon_s$ and has $s = 1, ..., \hat{s}$ denotes the schools, with $\hat{s}$ the total number of schools, n_s the number of observations in a school, and $N = \sum_{s=1}^{\hat{s}} n_s$ the total sample size. ϵ_s is an i.i.d error component with zero mean and variance σ_0^2. $\mathbf{l}$ is a vector of ones and κ_s the school intercept. $\mathbf{Y}$ is the $N \times 1$ vector of outcomes and $\mathbf{X}$ is the $N \times k$ matrix of variables that include family ideals, the controls, and, in the case of the GPA model, own-attitudes about a school. λ is the endogenous social interaction effect—network effect—corresponding in the theory section to δ_p or θ_p. Again, $\mathbf{W}$ is row-normalized, thus $\mathbf{WY}$ returns the weighted average of the peer dependent variable. β is the $k \times 1$ vector of coefficients.

The weighted average peer variables corresponding to those in $\mathbf{X}$ are introduced as the lag of $\mathbf{X}$ by $\mathbf{WX}$ with ϕ the vector of corresponding coefficients.

Weighted average peer variables enter the model because the literature distinguishes between social interaction effects through λ and contextual peer effects. Ignoring the GNS with fixed effects risks bias to estimates of the included parameters, because of potential endogenous, contextual, and correlated effects, unless an excluded component can be justified with a zero effect. In the absence of social interaction effects global spill-overs through the network do not exist, but local spill-overs from contextual effects may.[6]

A variety of other spatial models can be obtained from the GNS model by restricting parameters to zero. Elhorst (2014) provides a full accounting for the taxonomy of spatial models. I explored and compared these spatial models and conclude on presenting the Spatial Durbin Model (SDM)—which sets $\rho = 0$—and the GNS model. Both of these models importantly include endogenous and contextual effects.

Average peer attitudes are omitted from the GPA model. Average effort in the peer group is expected to track with the average attitudes, because both form measures that in the theory match an ideal in the peer group expressed as a prototypical choice (effort) or trait (attitudes). Thus, average performance in school by the peer group will track with the average peer group attitudes. In the empirics, this means average peer attitudes and average peer performance may be collinear. I choose the average peer performance in the performance model and average peer attitudes in the attitudes model for the empirics to match the theory and to capture the simultaneity that arises from these actions occurring on a network that can lead to global spill-overs in the network. Own-attitudes enters as a key explanatory variable to a school performance model as motivated in the theory, and excluding peer average attitudes from the performance model, is theoretically motivated.

6. See Elhorst (2014), Epple and Romano (2011) and Manski (1993) for further detail.

Estimation is by quasi maximum likelihood (QML). To illustrate the method for quasi-maximum likelihood estimation, I present the estimator, with group fixed effects included only at the school level.

The reduced form of equation 4.1 (dropping the s subscript for simplicity) is $\mathbf{Y} = \mathbf{S}^{-1}(\mathbf{Z}\boldsymbol{\delta}_0 + \mathbf{R}^{-1}\boldsymbol{\epsilon})$, where $\mathbf{S} = (\mathbf{I} - \lambda\mathbf{W})$, $\mathbf{Z} = (\mathbf{l}, \mathbf{X}, \mathbf{WX})$, $\delta_0 = (\kappa, \beta', \phi')$, and $\mathbf{R} = (\mathbf{I} - \rho\mathbf{W})$. It is constructive to note that an expansion of $\mathbf{S}^{-1}$ yields

$$\mathbf{S}^{-1} = \sum_{j=0}^{\infty}(\lambda_0\mathbf{W})^j = \mathbf{I} + \lambda\mathbf{W} + \lambda^2\mathbf{W}^2 + ...,$$

and given a row normalized weights matrix this implies the restriction that $\lambda \in (-1, 1)$ else identification fails (Lesage and Pace 2009). A Cochrane-Orcutt type transformation frees the disturbance term from the spatial correlation component allowing the model to be expressed as

$$\mathbf{RSY} = \mathbf{RZ}\boldsymbol{\delta}_0 + \boldsymbol{\epsilon}. \tag{4.2}$$

Now let the full parameter vector be $\boldsymbol{\theta} = (\boldsymbol{\delta}_0', \lambda, \rho)'$ and $\boldsymbol{\epsilon} = \mathbf{R}(\mathbf{SY} - \mathbf{Z}\boldsymbol{\delta}_0)$. Assuming that $\boldsymbol{\epsilon} \sim N(0, \sigma^2)$ the maximum log-likelihood estimator of 2.2 is

$$LL(\boldsymbol{\theta}) = -\frac{n}{2}\, ln\, (2\pi\sigma^2) + \sum_{s=1}^{\bar{s}} ln\, ||\mathbf{S}|| + \sum_{s=1}^{\bar{s}} ln\, ||\mathbf{R}|| - \frac{1}{2\sigma^2}\sum_{s=1}^{\bar{s}} \boldsymbol{\epsilon}'\boldsymbol{\epsilon}. \tag{4.3}$$

Estimation of the spatial parameters λ and ρ is simplified by first concentrating 4.3 through maximizing with respect to $\boldsymbol{\delta}_0$ and σ^2 and using the closed form solutions to $\hat{\boldsymbol{\delta}}_0$ and $\hat{\sigma}^2$ to reduce 4.3 to a function of λ and ρ. The first order conditions of 4.3 with respect to $\boldsymbol{\delta}_0$ and ρ are as follows:

$$\frac{\partial LL}{\partial \boldsymbol{\delta}_0} = -\frac{1}{2\sigma^2}(\mathbf{Z}'\mathbf{R}'\mathbf{R}(\mathbf{SY} - \mathbf{Z}\boldsymbol{\delta}_0) = 0$$

and

$$\frac{\partial LL}{\partial \sigma^2} = -\frac{n}{2\sigma^2} + \frac{1}{2\sigma^4}\boldsymbol{\epsilon}'\boldsymbol{\epsilon} = 0.$$

Solving we can find that $\hat{\boldsymbol{\delta}}_0 = (\mathbf{Z}'\mathbf{R}'\mathbf{R}\mathbf{Z})^{-1}\mathbf{Z}\mathbf{R}'\mathbf{R}\mathbf{S}\mathbf{Y}$ and using $\hat{\boldsymbol{\delta}}_0$ to solve for $\hat{\sigma}^2$ we can find that $\hat{\sigma}^2 = \frac{1}{n}\mathbf{Y}'\mathbf{S}'\mathbf{R}'\mathbf{P}\mathbf{R}\mathbf{S}\mathbf{Y}$, where $\mathbf{P} = \mathbf{I} - \mathbf{R}\mathbf{Z}(\mathbf{Z}'\mathbf{R}'\mathbf{R}\mathbf{Z})^{-1}\mathbf{Z}'\mathbf{R}'$. Lesage and Pace (2009) makes an instructive point for the model that omits ρ, which can be extended here. Supposing we knew the parameter values of λ and ρ we can estimate the remaining parameters with simple OLS as evidenced by $\hat{\boldsymbol{\delta}}_0$. Therefore, concentrating out $\boldsymbol{\delta}_0$ and ρ and obtaining the concentrated likelihood function in terms of $\boldsymbol{\gamma} = (\lambda, \rho)'$ allows first estimating $\boldsymbol{\gamma}$ and then using those estimates to estimate $\hat{\boldsymbol{\delta}}_0$ with a basic regression. To obtain the concentrated likelihood function, input the closed form expressions for $\hat{\boldsymbol{\delta}}_0$ and $\hat{\sigma}^2$ giving

$$\begin{aligned} LL(\boldsymbol{\gamma}) = &-\frac{n}{2}\, ln\, (2\pi\hat{\sigma}^2(\boldsymbol{\gamma})) + \sum_{s=1}^{\bar{s}} ln\, ||\mathbf{S}|| + \sum_{s=1}^{\bar{s}} ln\, ||\mathbf{R}|| \\ &- \frac{1}{2\hat{\sigma}^2(\boldsymbol{\gamma})}\sum_{s=1}^{\bar{s}} (\mathbf{S}\mathbf{Y} - \mathbf{Z}\hat{\boldsymbol{\delta}}_0)'\mathbf{R}'\mathbf{R}(\mathbf{S}\mathbf{Y} - \mathbf{Z}\hat{\boldsymbol{\delta}}_0). \end{aligned}$$

This expression reduces to a function of $\boldsymbol{\gamma}$ and a constant term k that does not depend on $\boldsymbol{\gamma}$. The concentrated log-likelihood is a partial likelihood and given by

$$LL(\boldsymbol{\gamma}) = k - \frac{n}{2}\, ln\, \hat{\sigma}^2(\boldsymbol{\gamma}) + ln\, \sum_{s=1}^{\bar{s}} ||\mathbf{S}|| + ln\, \sum_{s=1}^{\bar{s}} ||\mathbf{R}||. \tag{4.4}$$

The quasi-maximum likelihood estimates for $\boldsymbol{\gamma}$ from 2.3 can now be obtained and in turn used to obtain estimates for $\boldsymbol{\delta}_0$.[7]

7. See Lesage and Pace (2009), Lee, Liu, and Lin (2010), and Burridge, Elhorst, and Zigova (2014) for more on the concentrated likelihood function in its different forms for different spatial models. Lee, Liu, and Lin (2010) provide formal proofs of identification and asymptotic results for the GNS social interaction model, with a row-normalized spatial weight matrix, and homoskedastic errors. Methods other than ML exist to include generalized spatial two-stage least squares (GS2SLS), generalized method of moments (GMM), and Bayesian techniques. See Kelejian and Prucha (1998), Lee (2003), Lee (2007b), Liu, Lee, and Bollinger (2010), and Lesage and Pace (2009) for more details on alternative estimation methods.

A primary difficulty is the calculation of the derivatives for the logged determinant terms and the assumption of constant variance across spatial units. Lesage and Pace (2009) provide an overview of methods for these calculations and multiple software packages now contain routines to estimate the QML model with homoskedastic errors. In the case of heteroskedastic errors, Burridge, Elhorst, and Zigova (2014) note that closed form solutions from the unconcentrated log-likelihood function in 4.3 are no longer available. Kelejian and Prucha (2010) develop the generalized spatial two-stage least squares (GS2SLS) approach, along with a generalized method of moments routine for the calculation of ρ, in the presence of heteroskedastic errors. The tradeoff, noted in footnote 15 of Lee, Liu, and Lin (2010), is that relying on the lagged X variables for instruments may result in weak identification with weak WX instruments and the results can be sensitive to interaction between the instruments and model specification. Burridge, Elhorst, and Zigova (2014) discuss an ML extension for heteroskedasticity in the GNS model but do not extend it to the case of group fixed effects. Lesage and Pace (2009) put heavy emphasis on Bayesian approaches for spatial models with heteroskedasticity but do not consider those in the case of the GNS model. Neither Lin (2010) nor Lin (2015) in peer effects application papers using the GNS model mention heteroskedasticity. Thus, the econometric state of accounting for heteroskedasticity in a peer effects model is still young and worth considering further in the future.

4.2.2 Interpretation

Parameter interpretation in spatial models is more complicated than with a typical regression model. Write the reduced form of the GNS model in 4.1 as

$$\mathbf{Y} = (\mathbf{I} - \lambda\mathbf{W})^{-1}(\mathbf{X}\beta + \mathbf{W}\mathbf{X}\phi) + \mathbf{V}, \tag{4.5}$$

where $\mathbf{V}$ contains the school intercepts and error terms. The identity matrix, $\mathbf{I}$, is $N \times N$.[8]

8. I drop the *s* subscript for simplicity.

Taking the derivative for the expected value of $\mathbf{Y}$ with respect to the *k*th explanatory variable returns

$$\frac{\partial E(\mathbf{Y})}{\partial x_{ik}} = (\mathbf{I} - \lambda \mathbf{W})^{-1}(\mathbf{I}\beta_k + \mathbf{W}\phi_k). \tag{4.6}$$

The expression in 4.6 is the empirical counterpart to the theoretical network profile of NE in 3.4. Taking the derivative of 4.5 for the *k*th variable and all adolescents in the sample returns the matrix of partial derivatives (Elhorst 2014)

$$\left[\frac{\partial E(\mathbf{Y})}{\partial x_{1k}} \cdots \frac{\partial E(\mathbf{Y})}{\partial x_{nk}}\right] = (\mathbf{I} - \lambda \mathbf{W})^{-1} \begin{bmatrix} \beta_k & w_{12}\phi_k & \cdot & w_{1N}\phi_k \\ w_{21}\phi_k & \beta_k & \cdot & w_{2N}\phi_k \\ \cdot & \cdot & \cdot & \cdot \\ w_{N1}\phi_k & \cdot & \cdot & \beta_k \end{bmatrix}. \tag{4.7}$$

The expression in 4.7 is a matrix of partial effects for the *k*th variable that gives the direct effects on the diagonal, indirect effects off the diagonal, and total effects as either the row or column sum multiplied by $(\mathbf{I} - \lambda \mathbf{W})^{-1}$, which is sometimes referred to as the spatial or, in this case, social multiplier. These are taken for each individual spatial unit, adolescent in my data, thus the marginal effects can differ across people. Lesage and Pace (2009) recommend reporting the average of the direct effects on the diagonal and the average of the row or column sums for the average total effects that includes both the direct and indirect effects.[9] The row sum in 4.7 gives the total impact on *i*'s outcome that occurs from changing an independent variable by the same amount across all observations in a network. A column sum gives the total impact on the outcomes of all individuals in the network that occur from a change in an independent variable for a single, *j*th observation. It turns out that the row and column sums are equal and only the chosen interpretation that differs.[10]

9. In the case of own-attitudes in the GPA model, average peer attitudes is omitted therefore the off-diagonals of 4.7 are all zero and spill-over effects only run through the social multiplier matrix for a change in own-attitudes.

10. See Lesage and Pace (2009) for a detailed accounting of this fact.

The average direct effect provides the estimated average impact on an individual's dependent variable for a change in an independent variable. For example, the average direct effect for own-attitudes in the GPA model will provide the estimated average impact on an adolescent's GPA for a one unit change in attitudes. The average direct effect includes the feedback effects that return to the adolescent through the simultaneity and through the spatial lag in the explanatory variable. Finally, taking the difference between the average total effect and the average direct effect gives the average indirect effect.

Indirect effects are the social spill-overs. Social spill-overs are impacts on the outcomes of those linked to an adolescent *i*, running from a change in a variable for *i* to those linked in the network. For instance, the indirect effect of a change in the attitudes of adolescent *i* is the spill-over effect to those directly linked to *i* and then on to those linked with *i*'s peers and so forth. This can be summed up as the impacts $x_{ik} \rightarrow y_j$. The average indirect effects represent cumulative average impacts over the network (not including *i*) from a change in x_{ik}. Therefore, estimates of indirect effects can be larger than direct effects, but keep in mind that it is an estimate of the average cumulative spill-over in the network from a change in x_{ik}.[11] In an attitudes model, the effect of peer attitudes (λ) will test for the network effects in attitudes that create spill-over effects suggested in the theory. Average direct effects allow testing for the influence of transmitted family ideals—as proxied by parental college disappointment—in shaping an adolescent's attitudes about school. The indirect effect estimates for family ideals then test for the presence of spill-overs in attitudes from changes in family ideals. Because I use indicators of parental college disappointment to proxy the family ideals, the low indicators are expected to have negative average direct and indirect effects and the high indicators positive average direct and indirect effects. Combined this links the spatial econometric empirical model to the theoretical model for production of own-attitudes. Moreover, testing for direct and indirect effects from changes in family expectations tests whether the family influence creates spill-overs by working through the presence of peer effects. It does

11. For a more detailed explanation of the indirect effect estimates as average cumulative effect estimates over the network see LeSage and Dominguez (2012) and Lesage and Pace (2009).

so by exploring whether changes in family expectations have influence to other adolescents in a school through the presence of endogenous peer effects. This not a test of moderating effects. Rather, it is a test of spill-overs in the presence of peer effects when the change in the independent variable is strong enough.

In a GPA model, the effect of peer GPA (λ) will test for the network effects in GPA consistent with a conforming effect suggested in the theory. Average direct effects allow testing for the influence of own-attitudes on performance. A positive estimate will be consistent with the theory and suggest family and peer influence on own-attitudes will affect performance in school. Also, average direct effects can examine the influence of family college disappointment as a conforming effect. Average indirect effects will test for spill-overs in performance across a school-network for changes in own-attitudes and changes in family college disappointment. Combined this links the spatial econometric empirical model to the theoretical model for choice of effort.

In chapter 2 and 3 I discuss how family and peer group ideals may combine or compete. The above discussion on spatial partial effects, especially indirect effects, setups up how I can explore the consequences of a change in parental expectations, my proxy for family ideals, that because of the addition of peer networks in a school may generate spillovers in the network. This holds constant any other change in the peer group that will also create influence through peer effects. In that sense it tests whether family influence has multiplier effects because of peers. However, in the case that peer effects are present, it also informs us that any other change working through the peer group can compete with the family effect on adolescent.

For example, consider an adolescent named John whose parents attend a workshop on financial aid and then raise their collegiate expectations. If that has a positive influence on John's attitudes, then John positively influences his peers' attitudes in the presence of social interaction effects, holding all else constant. However, because of these social interaction effects if something else also changes among the peers then John will recieve spillovers in reverse. For example, suppose Sally and Tim are John's friends and they hang out in a group. They begin to feel rejected at their school and are convinced that the teachers are out to get them. This lowers their attitudes

about school and they see themselves in opposition to academics. Because, of social interaction effects when John deviates by raising his attitudes in response to his parent's expectations he is pulled in two different directions. Thus, in this case the two groups compete in terms of their conforming influences. John's spillover to Sally and Tim may not be large enough to overcome their feeling of being outcasts at the school. Exploring for evidence of social interaction effects, direct effects from parental educational expectations, and indirect effects from parental educational expectations allows me to more generally explore this story. If all three are present, then it is indeed possible for their to be combined and/or competing effects from family and peer groups.

4.3 Identification

4.3.1 Peer Effects

Identification of peer effects faces a number of concerns. Simultaneity from including the weighted average of peer outcomes introduces linear dependence between peer outcomes and peer characteristics. Manski (1993) dubs this the "reflection problem". Lack of identification results from large group means defining the peer average outcome. As a result, there is little, or no, variation in peer group means over the sample. The effect of peer average outcomes (the endogenous effect) and peer contextual effects cannot be separately identified. Network data, however, can break the linear dependence between peer outcomes and peer characteristics. Variation in the interaction groups is critical. Lee (2007a) studying the use of spatial econometric models for peer effects shows that with more variation identification is stronger. With network data defining the individual's reference group, average peer outcomes and characteristics are now specific to the individual. Bramoullé, Djebbari, and Fortin (2009) formally show that the "reflection problem" is solved in the presence of second order peers linked to first order peers but not to the individual.[12] Extend-

12. This implies intransitive triads such that for the set of *i*,*j*,*k* people where $\{i, j\}$ and $\{j, k\}$ are linked persons i and k are not linked. Without unobserved heterogeneity, this means that if $\mathbf{I}$, $\mathbf{W}$, and $\mathbf{W}^2$ are linearly independent social effects are identified. Bramoullé, Djebbari, and Fortin (2009) also show that $\mathbf{I}$, $\mathbf{W}$, $\mathbf{W}^2$, and $\mathbf{W}^3$ must be linearly independent when controlling for correlated effects for identification to hold.

ing to control for correlated effects requires the existence of third order peers for identification to hold. I have checked my data by school-network and these conditions hold.

Correlated effects from shared environments and peer group selection are additional threats to the identification of peer effects (Epple and Romano 2011). Leaving correlated effects unaccounted for may lead the researcher to believe they have estimated peer effects, when in reality the outcomes of individuals and peers are similar because of unobserved, shared environments that affect the dependent variable. I include school fixed effects to control for shared environments and estimate the spatial correlation component to potentially control for unobserved heterogeneity in peer selection.

It is possible a school may consist of multiple macro-group structures such that all members of the macro-group can be connected by a path of some length. Fixed effects at the macro-group level suffer from the incidental parameters problems. This occurs because the number of macro-group fixed effects will grow at the same rate as the sample size. Lee, Liu, and Lin (2010) introduce a panel like within transformation to avoid this problem. However, Burridge, Elhorst, and Zigova (2014) find that this can introduce multi-collinearity and reject the GNS model with macro-group fixed effects in comparison to other spatial models with their data. Therefore, I include the school fixed effect to capture correlated environmental effects at the school level but this may leave some macro-group heterogeneity unaccounted for.[13]

Moffit (2001) points out that correlated effects can also arise from omitted variables that represent the friendship selection process. Spatial econometrics makes it possible to estimate correlation in the error terms between spatial units—adolescents in this case—that varies at the group level. Lee, Liu, and Lin (2010) suggest that controlling for this correlation component (ρ) can reduce some of the bias from a misspecified model, as far as there are omitted variables related to

13. As will be seen in the results, estimation of the endogenous effect, λ, in the GPA model turns out to be strikingly similar to its estimation in Lin (2010) who uses the panel like within transformation proposed by Lee, Liu, and Lin (2010) at the school-grade level and the full Add Health sample, thus unobserved correlated effects at a lower level than the school fixed effect appears to not be an issue.

self-selection into peer groups. Games of complements played on networks suggest environments where peer effects exist naturally imply spatial dependence.

The spatial dependence is tied through the endogenous effect of peer behavior, contextual effects, and the potential correlated effects in the error term. Each individual is impacted by their reference group. With schooling and friendship, the reference group sensibly results from a process of self-selection into a friend group. The correlated spatial dependence now represents both impacts from common shocks and selection effects based on shared tastes and preferences (though it may not capture all of the effects from self-selection; see Lee, Liu, and Lin (2010) for more detail). If there exists friend group selection around shared preferences for the dependent variable in question, then failing to control for this spatial correlation will result in upward bias of the endogenous effect parameter. For example, in this case, positive correlation in grades resulting from similar preferences for school performance will be missatributed to the performance of peers which increases the estimated peer effect. Whereas, if there exists group selection around other behaviors, instead of the one under study, then failing to control for spatial correlation can still result in a bias to the peer effect and may even result in a downward bias.

For example, suppose unobservable preferences that determine peer group selection bring peers together who have dissimilar unobservables in school performance conditional on peer performance. Now, the residuals between peers will be negatively correlated in a performance model and decrease the estimated effect of peer performance on own-performance. In essence, this would be a case of distance between peers in terms of grades because of unobservables that once controlled for indicate the influence of peer grades is actually stronger.

Where network theory literature informs interpretation of estimated effects, the spatial econometrics literature has made advances regarding how those estimates can be obtained in face of the "reflection problem" and unobserved correlated effects. Additionally, Add Health provides a rich set of characteristics that may relate to peer group selection and which I include in the control variables.

Later, I consider an alternative method for estimating the endogenous peer effect. The results of Bramoullé, Djebbari, and Fortin (2009) imply that indirect links (peers of peers) form natural exclusion restrictions. Thus, I use the characteristics of peers of peers as instruments for the endogenous peer effect, to compare against those of the spatial models with the spatial correlation term.

4.3.2 Attitudes and Family Ideals

The theoretical framework from chapter 3 and the empirical framework of this chapter for the attitudes model assumes that current period GPA does not determine the individual's current period attitudes about school. Grades from previous periods may reasonably play a role in building attitudes about academics through motivation or confidence. The influence of past period GPA could be captured by a confidence variable. If none exists and past period GPA is not available, then there is an omitted variables problem. Ability, however, may hurt confidence through preventing a person from doing well or help confidence in the opposite case. We know that IQ is rank stable after the age of 10 (Heckman and Mosso 2014), so variation in current period attitudes from confidence in one's ability may be captured in an ability proxy for adolescents. I include the Add Health Peabody Picture Vocabulary test scores as an ability proxy.

Parental educational expectations may still be simultaneously determined with an adolescents own-attitudes and performance. I recognize this point. In this study, I descriptively explore the role of these educational expectations and focus identification on the peer effects and on the effect of attitudes on school performance. Disentangling the relationship between parental expectations and adolescent attitudes, or other outcomes, is for future work.

As a possible test for the impact of attitudes on performance free of simultaneity, I use data from wave II in robustness checks and explore the impact of the previous period attitudes on wave II GPA.[14] Furthermore, I consider past period attitudes as instruments for the effect of current period attitudes. These checks are presented with caution, because bias from serial correlation

14. The last wave for the high school period of Add Health respondents.

between periods cannot be ruled out and a third wave of high school data does not exist to appropriately instrument for the time lagged effects[15] Finally, I check the effect of attitudes on years of educational attainment drawn from wave four of the data, the last available wave. This last check removes simultaneity and aims to offer an alternative measure of effort.

Estimated effects for family ideal indicators could suffer from unobserved adolescent ability, unobserved heterogeneity in the family background, and potential simultaneity with the adolescent's attitudes or performance. An ability proxy is included for the first issue and several measures for family background effects are included to control for the second issue. For the case of simultaneity, I argue that the adolescent's attitudes are unlikely to predict the families academic ideals unless parents are adjusting their ideals to their children's behavior. More likely parent's adjust their enforcement of ideals to the behavior, when holding constant ability.

4.4 Data and Methods Summary

In this chapter, details on the data, variable creation, spatial econometric methods, and identification have been discussed in the context of studying family and peer influences on schooing attitudes and performance. Data from Add Health provides the ability to proxy family ideals as educational expectations and to observe the peers an adolescent identifies with. Furthermore, a range of questions feasibly allows proxying an adolescent's attitudes about school.

I use spatial econometrics to test both direct and spill-over effects suggested by the theory. Spatial model partial effects closely match the profiles of Nash Equilibria derived in the theory of two groups in the previous chapter. Thus, the Add Health Data operationalizes the key theory variables and spatial econometrics facilitates testing it.

15. See Bond (2002) for a review of dynamic panel data models with micro data.

CHAPTER V
DESCRIPTIVE ANALYSES

This chapter explores descriptive relationships between the key variables of interest. These were motivated in the theory chapter and discussed operationally in the data and methods chapter. The factor score variable I relate to attitudes about school was constructed mean zero with a standard deviation of one from reports of desire for college, how likely the respondent thinks they will go to college, feeling apart of the school, happy at school, feeling teachers are fair, and feeling close to people at school for own-attitudes, as discussed in the data and methods chapter. Hereafter, I simply refer to it as attitudes or own-attitudes. Family ideals are proxied by the indicators constructed from parental college disappointment and self-reported grade point average (GPA) proxies effort in school. Where useful, I provide descriptive relationships from both the full sample of the saturated schools post-listwise deletion of missing data and the sample post-construction of the directed graph spatial weights matrix. In all cases, the descriptive patterns of interest do not change with the loss of data. For conciseness and ease of comparison, I present these side by side but the focus is on exploring the descriptive associations.

In general, the descriptive analyses show that the variables and data selected have variation consistent with my expectations from the theory. We do not directly observe family or peer ideals. To proxy these concepts can be admittedly difficult. I bring expectations to the data from the theoretical component of this dissertation. The data and variables from Add Health appear to descriptively match some of those expectations, motivating the study of the spatial econometric results in the next chapter.

The four key components are parental collegiate expectations, attitudes about school, performance in school, and peer effects. Five points are drawn from the descriptive analysis to explore these key components. I first present evidence consistent with theoretical expectations on

the associations between parental expectations and attitudes about school and performance in school. Second, there is a positive correlation between own-attitudes about school and performance. Third, attitudes are positively related to peer attitudes and GPA to peer GPA. Also, when split over parental expectations it appears that as parental expectations move from low to high adolescents have better attitudes for a given average of peer attitudes. Thus, those with low parental expectations and low peer attitudes have much lower attitudes about school than any other group. This pattern is repeated, though less drastically, for GPA. Fifth, the association between GPA and peer GPA shifts down for those with below average attitudes about school, which indicates that own-attitudes is still correlated with performance when conditioning on peer performance as expected.

5.1 Empirical Distributions of Attitudes and GPA by Parental Collegiate Expectations

Figures 5 and 6 explore the empirical densities of own-attitudes about school and GPA by indicators for parental college disappointment. Both present the same graphic from the full sample (left panel) and the sample post-construction of the directed graph spatial weights matrix (right panel), as a quick check against the loss of observations in the sample with the directed graph. The primary point here is that parental expectations are related to attitudes in a manner consistent with the theory.

In figure 5, the patterns between both panels are the same. Differences in the distribution of attitudes by parental college disappointment do not appear to be affected by the loss of observations after construction of the spatial weights matrix.

Parental college disappointment is the selected proxy for ideals on education transmitted by the family to the respondent. In the theoretical model, lower family ideals lower an adolescent's malleable attitudes about school. Figure 5 shows a descriptive story consistent with this expectation. The empirical density of attitudes shifts to the right—towards better attitudes—as parental expectation for college rise. Having either one or two parents with low expectations corresponds with a much higher density over poor attitudes, than either one or two parents in the high cate-

gories. Having parents in the middle, say neutral expectations, splits the difference between the low and high categories. Descriptively, adolescents with parents who indicate higher expectations are more likely to have better attitudes about school.

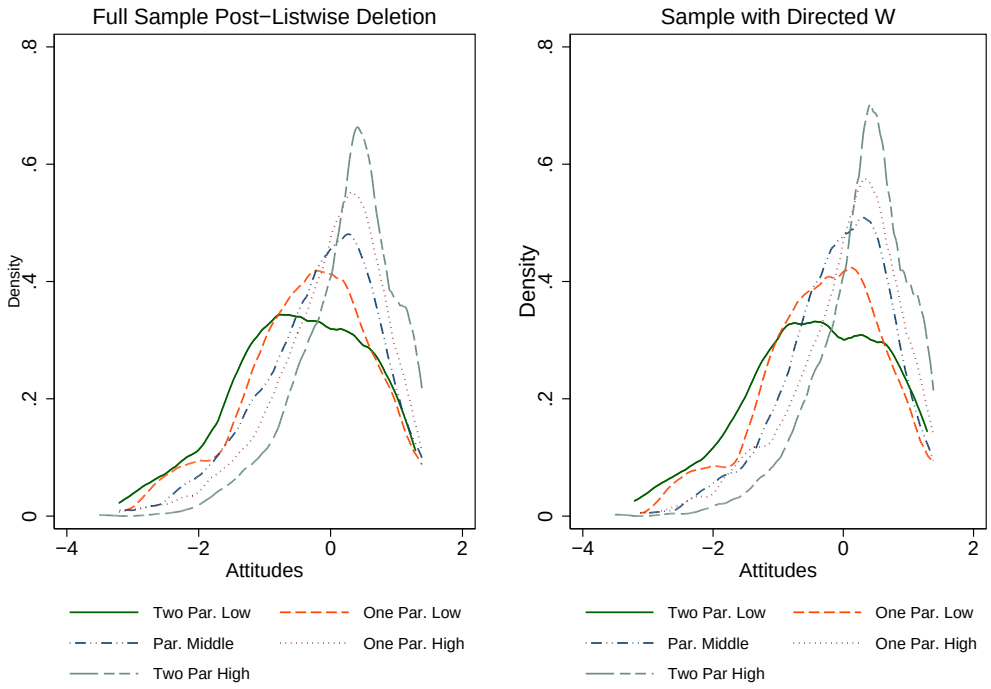

Figure 5. Density of Attitudes Index by Parental College Disappointment Categories

Figure 6 shows the empirical density for adolescent GPA by parental college disappointment indicators. It too indicates that the differences between level of parental expectations do not change much from the loss of observations in the sample post-construction of the spatial weights matrix. The differences by parental expectations are again as expected with the empirical density of GPA improving as parental expectations increase. While not as pronounced as in figure 5, these differences show there is variation in performance by level of parental collegiate expectations.

In figure 6, adolescent's with two parent's in the high expectations category have markedly stronger performance. This, of course, could result from a variety of other factors, but it does appear to suggest that it is important to break down parental college disappointment into indicators

that account for whether collegiate expectations are the same or different in a family. Also, on the low expectations side having one parent in the low category returns an empirical distribution shifted to the left of two parents in the low category. On the whole, GPA densities for the one parent low and two parent low categories are worse than other categories as expected. Why the one parent low category is further left than the two is not entirely clear, but it may simply result from additional factors in single parent homes who all enter on the one parent low, one parent high, or middle indicators. This can be controlled for in the empirical models.

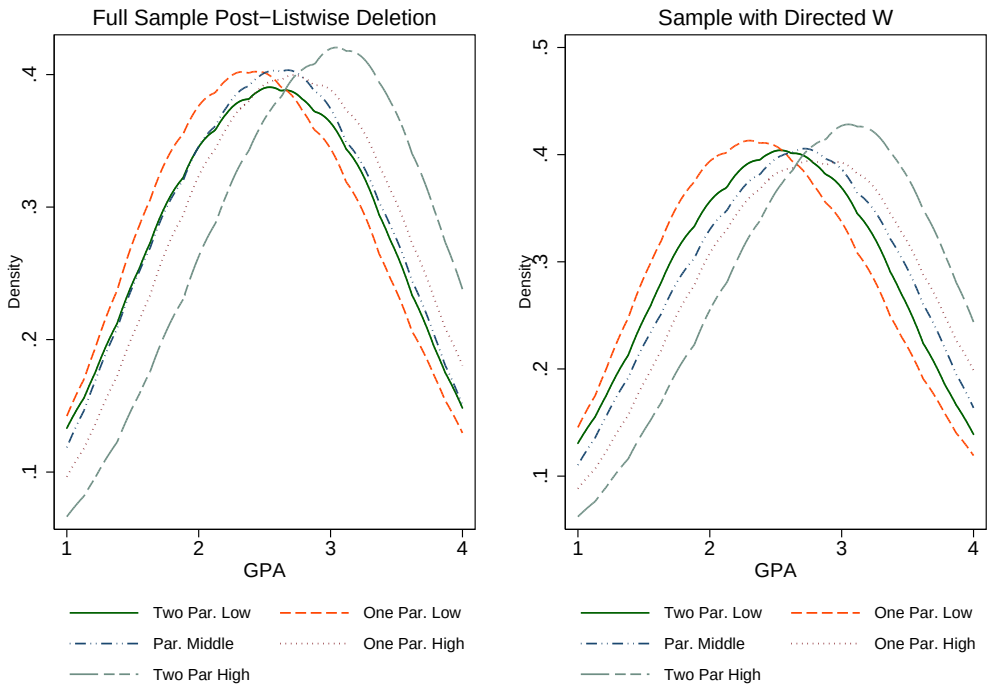

Figure 6. Density of GPA by Parental College Disappointment Categories

5.2 Associations Between GPA, Attitudes, and Peer Outcomes

Figure 7 shows the simple association between GPA and own-attitudes. Stata's binscatter command was used to construct the graphs. Each dot represents the mean of equal sized bins of observations. The left panel is from the full sample and the right panel the sample with the spatial

weights matrix. The results are qualitatively unchanged. Both panels show a clear linear association between GPA and own-attitudes. This is consistent with my expectations from the theory. Recall that in the theory model own-attitudes positively impacts effort by lowering the cost of effort. Adolescents on the lower end of the attitudes distribution are associated with much worse school performance than those on the higher. Furthermore, having very high attitudes is associated with very strong performance.

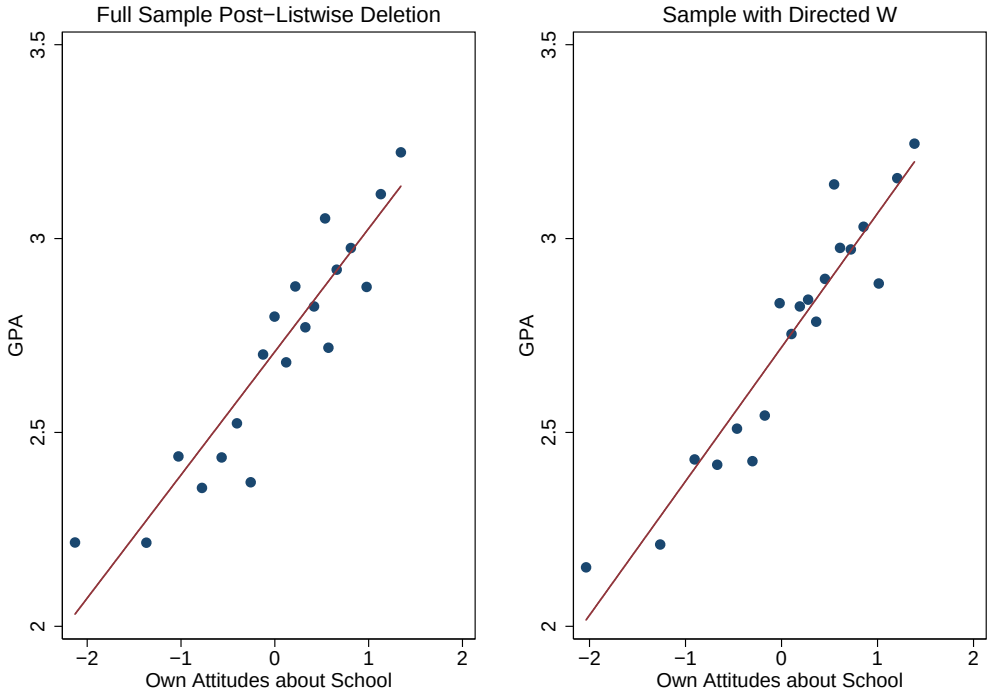

Figure 7. Descriptive Association Between GPA and Own-Attitudes

Figure 8 explores the descriptive relationships between attitudes and peer average attitudes in the left panel and GPA and peer average GPA in the right panel. In each case, the relationships are delineated by parental collegiate expectations and estimated with the Lowess smoothing estimator. Attitudes are positively associated with peer attitudes and GPA with peer GPA for every level of parental expectations. In the left panel of figure 8, parental collegiate expectations shifts the trend line between attitudes and peer attitudes up as the expectations increase. It appears that

parental expectations may combine with or compete against peer attitudes. Adolescents with families in the high college disappointment categories but with peers who have poor attitudes are associated with considerably worse attitudes. Their attitudes are much better than adolescents with low parental expectations and low average peer attitudes. But, their attitudes are much worse than adolescents with high parental expectations and high average peer attitudes. Adolescents for whom families have low expectations and average peer attitudes are low are associated with markedly worse attitudes than any other group. There does appear to be some convergence towards the extreme end of average peer attitudes. However, because of a small numbers of observations at the extreme ends of the attitudes distribution not much can be assessed. At all levels of peer attitudes below one, the pattern holds as discussed.

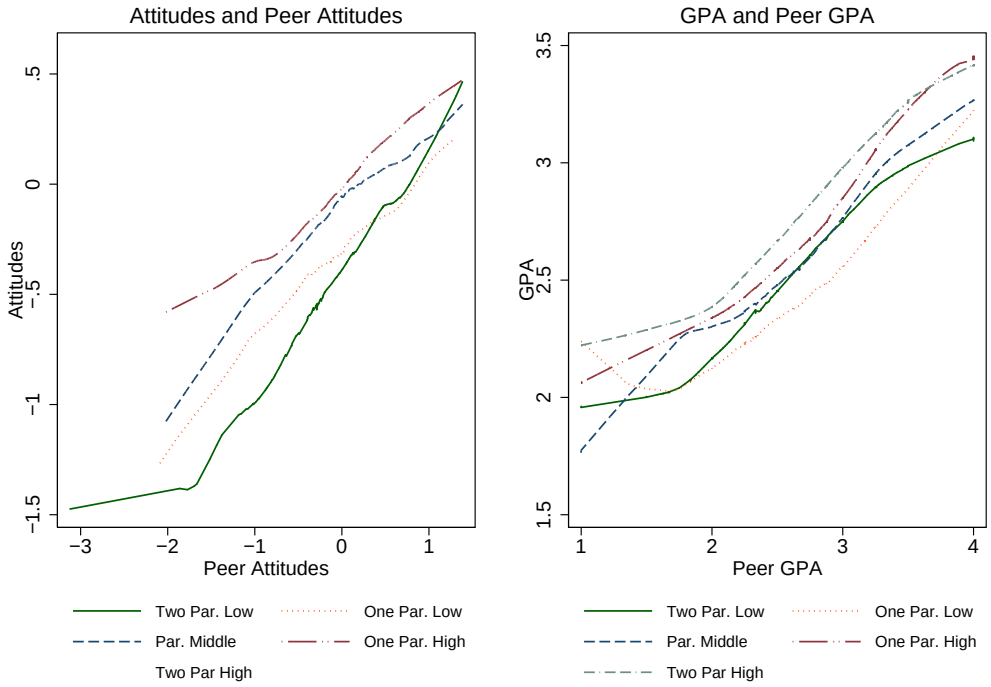

Figure 8. Descriptive Association Between Attitudes and Peer Attitudes and GPA and Peer GPA by Parental College Disappointment Indicators

In the right panel of figure 8, the pattern between parental collegiate expectations and the trend between GPA and average peer GPA is similar to that of attitudes, though not quite as pronounced—unless comparing the one parent low category with the two parent high category. Again, adolescents for whom families have stronger expectations and average peer performance is high are associated with the best performance. And, adolescents for whom families have the lowest expectations and average peer performance is low are associated with the worst performance. Overall, this is consistent with the theoretical implication that family ideals and peer group ideals may combine or compete. When both groups have high ideals, strong incentives are exerted for high effort, and when both groups have low ideals, strong incentives are exerted for low effort. Competing ideals result in incentives that push effort in different directions. The associations reported in figure 8 are consistent with this, but of course, may be the result of a variety of other factors.

Figure 9 plots GPA against average peer GPA by own-attitudes less than zero (the mean of the attitudes index) and own-attitudes greater than zero. With very poor peer performance, GPA is quite low, but it is substantially worse when own-attitudes are negative. At some points on the curve, the difference is as great as 0.5 GPA points. At very high levels of peer performance the difference does not appear to be so drastic, yet those with negative attitudes trail below those with positive attitudes.

The plotted associations in figure 9 are consistent with the hypothesis that own-attitudes—though possibly impacted by peer attitudes—can have independent effects from the peer group. Even very high peer performance does not remove the difference between negative and positive own-attitudes. Clearly, this is only descriptive but it is suggestive that peers and own-attitudes may have effects on performance in line with the expectations from the theory.

The descriptive analyses for the operationalized key variables matches expectations from theory. I observe consistent patterns between family college expectations and attitudes and fam-

ily college expectations and GPA with both the full sample post-listwise deletion of missing data and the smaller analyses sample post-construction of the directed graph spatial weights matrix. Associations between family college expectations and attitudes indicate higher expectations are correlated with better attitudes about school. Similarly, higher family expectations are correlated with better performance in school. Own-attitudes is strongly correlated with GPA. Peer attitudes and peer GPA are also strongly associated with own-attitudes and own-GPA. Finally, the negative correlation between poor attitudes about school and performance remains as peer GPA rises. This is consistent with own-attitudes being produced by multiple sources, not only the peers, and with a separate, individual effect for schooling attitudes on performance. Next, I turn to the spatial econometric empirical results.

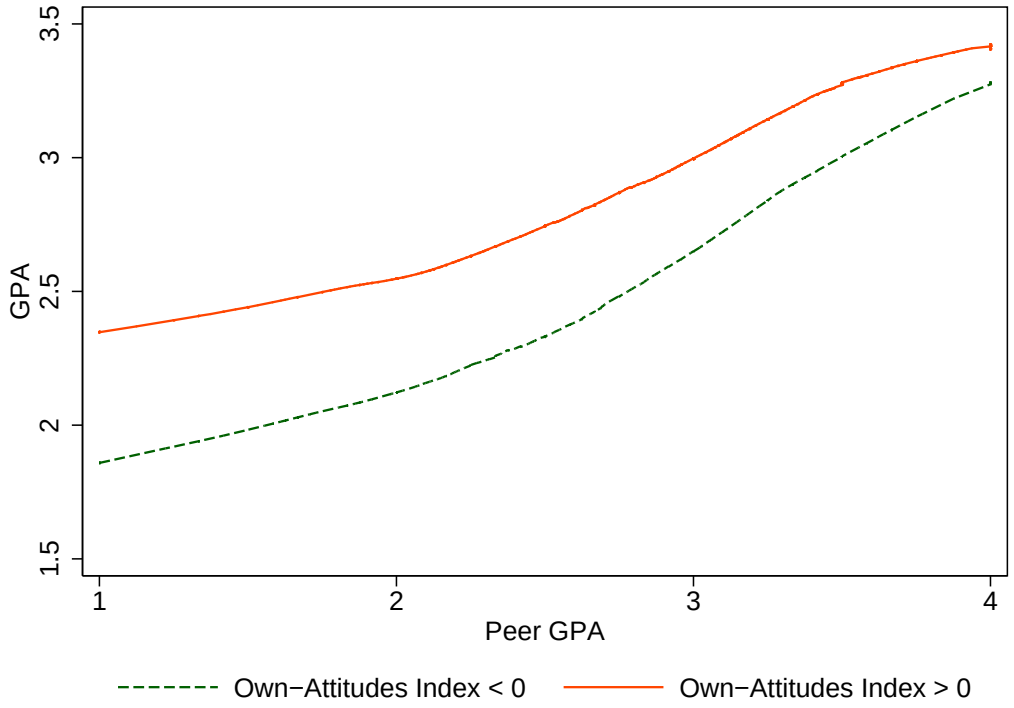

Figure 9. Descriptive Association Between GPA and Peer GPA by Adolescents with Negative or Positive Attitudes

CHAPTER VI

EMPIRICAL RESULTS

Using Add Health data, this chapter investigates results from the empirical model defined in chapter four linked to the theory in chapter three. Descriptive analyses in chapter five show that associations between respondents' report of expected parental college disappointment if they fail to graduate college (my proxy for family ideals) and the outcomes—own-attitudes about school and performance—are consistent with the theory. Chapter five also illustrated that GPA is correlated with own-attitudes and peer average GPA and that own-attitudes are correlated with peer attitudes. This chapter explores each of these points with the spatial econometric models described in chapter four. Furthermore, I test for spill-over effects, as discussed in the theory on two group identity influences (chapter 3), from changes in family college expectations and own-attitudes.

Spill-over effects in spatial models are not simply the coefficient estimates on lagged peer variables. As discussed and shown in chapter four, the partial effects from spatial models include social multiplier effects from the endogenous social interaction effect of the average outcome among the peers multiplied against the individual level and lagged peer covariates (sometimes called contextual peer effects). I use the direct, indirect, and total effects suggested by Lesage and Pace (2009) and defined in chapter four to interpret the main spatial model results. Again, the direct effect from a change in a variable on the outcome includes both the influence that is solely individual and the network effect that goes out through the network and returns influence back to the individual through simultaneity. The indirect effect is the average influence from a change in a variable for an individual out across the network. The total effect is the overall average aggregate effect including the direct and indirect effects.

I present the general nesting and spatial Durbin models as the main models of interest. The peer effects literature reviewed in chapter two motivates the inclusion of lagged peer variables

in both outcomes and other covariates, and the spatial econometric literature applied to peer effects motivates the estimation of the spatial correlation term in the residuals. By including lagged peer variables in both the outcome and covariates multiple types of peer effects are allowed. Endogenous effects from simultaneity between one's own outcome and peer outcomes can create social multiplier effects—meaning that any change in a variable that impacts the dependent variable for some adolescents will create even stronger effects by influencing other adolescents. One adolescent's attitude about school improves from a change in the home environment, for example, then the presence of peer effects in attitudes implies improvement in the attitudes of those connected. Peer effects stemming from a change in one adolescent's home environment do not imply social multipler effects. For example, if the improvement in an adolescent's home environment also comes with increased school support from the family then other adolescents may be influenced as well, creating contextual effects.

In chapter four, I defined the general nesting spatial model, which includes all types of spatial effects. The spatial correlation term (ρ) may capture some unobserved variation from peer group selection around the dependent variable of interest.[1] The spatial Durbin model omits ρ but still includes endogenous and contextual peer effects. Therefore, I present the general nesting and spatial Durbin models to explore the impact of peer effects with and without the control for spatial correlation in the residuals between an adolescent and her peers. Other restrictions of the spatial models—discussed in chapter four—-were explored but in each case either the general nesting or spatial Durbin model returned a better fit of the data. Furthermore, the presence of a positive and significant effect from peer outcomes in both the attitudes and performance models and of some significant contextual peer variables is consistent with the presence of multiple types of peer effects as motivated in the larger peer effects literature. Thus, I conclude that the general nesting and spatial durbin models are the appropriate models to present based on the past literature, potential endogeniety problems from omitting them, and my results.

1. See Lee, Liu, and Lin (2010) and Lin (2015) for more discussion of this point.

The main findings from this chapter are largely consistent with theoretical predictions made for adolescent effort in school and the production of own-attitudes. Estimates on peer effects from GPA and own-attitudes are positive and significant, suggesting social multipliers in those models. This evidence is also consistent with conforming effects from peer group ideals and expectations as motivated in the theory. Additionally, family expectations on college are found to be highly important to the production of own-attitudes but less so in their direct effect on performance, suggesting that family ideals may work more to build attitudes and aspirations for education than to impart conforming incentives. Finally, the empirical evidence shows spill-over effects in a school-network from family college expectations exist, especially in the attitudes models, and the empirical evidence shows evidence for spill-overs from changes in own-attitudes for GPA. The results suggest that targeting mechanisms related to both family and peer ideals over education can positively impact an adolescent's educational attitudes and outcomes, and in turn, send effects across a school network.

6.1 Spatial Model Results

Table 4 presents the model results for GPA as the dependent variable in the first two columns and attitudes as the dependent variable in the last two columns. School fixed effects are included for all models to capture school-level correlated effects. For the primary model results in table 4, the endogenous effect for GPA and attitudes and the spatial correlation terms are the estimated parameters of interest. I leave consideration of the impact from changes in covariates to the partial effects.

Endogenous effects, in table 4, for average peer GPA are positive and highly significant. The endogenous effect in the GNS model is estimated to be 0.440 and the correlation component -0.249. This is consistent with previous research. Lin (2010) who estimates a GPA specification with the GNS model—but with a different specification from mine and using the entire Add Health sample—finds an endogenous effect of 0.473 with a correlation estimate of -0.237 in

her table 6. Her estimate for the endogenous effect in the SDM with fixed effects is also relatively similar to my SDM endogenous effect estimate.

The positive estimates for the endogenous effect implies that social multipliers are present in the network from changes in GPA. Further, identity theory suggests that the parameter estimate for average peer GPA proxies the incentives to conform to the peer group ideal, leading to complementary effects in GPA between the individual and the peers. The empirical presence of this effect provides evidence this occurs and that global spill-overs will occur from changes to variables that impact performance.

Average peer attitudes are omitted from the GPA model as described in the empirical model section. Models including it were estimated. Compared to models without average peer attitudes the estimate for the endogenous effect (peer average GPA) barely changed in either the SDM or the GNS. However, the parameter estimate on peer average attitudes is close to zero with a p-value above 0.9 in the SDM but slightly negative with a p-value less than 0.05 in the GNS. An OLS omitting the average peer GPA and including the average peer attitudes, returns a positive and highly significant effect for peer attitudes. Thus, when the endogenous effect is omitted the cofficient on peer average attitudes is positive and significant. Including peer GPA in the SDM, the coefficient on peer average attitudes is near zero and in the GNS, where the effect of peer average GPA increases in magnitude, the average peer attitude parameter estimate becomes negative and significant. Parameter estimates for other variables were not affected—to include own-attitudes. This supports the idea that average peer attitudes proxy the group ideal and the average peer GPA is an expression of that ideal, meaning they proxy the same thing and should not both be included.

Table 4. Spatial Models for GPA and Attitudes (W_1)

	GPA		Attitudes	
	(SDM)	(GNS)	(SDM)	(GNS)
	β / SE	β / SE	β / SE	β / SE
Endogenous Effect (Peer Avg. of D.V.)	0.237***	0.440***	0.193***	0.316***
	(0.023)	(0.041)	(0.024)	(0.067)
ρ		-0.249***		-0.140*
		(0.051)		(0.076)
Attitudes	0.206***	0.186***		
	(0.018)	(0.018)		
Parental Attitudes on College				
Two Parents in Low	-0.004	-0.007	-0.335***	-0.328***
	(0.066)	(0.066)	(0.076)	(0.076)
One Parent in Low	-0.090*	-0.094*	-0.222***	-0.213***
	(0.052)	(0.051)	(0.060)	(0.060)
One Parent in High	0.083*	0.086**	0.117**	0.115**
	(0.043)	(0.042)	(0.050)	(0.049)
Two Parents in High	0.084*	0.079*	0.249***	0.248***
	(0.047)	(0.047)	(0.055)	(0.055)
Controls				
Picture Vocabulary Test Scores	0.140***	0.138***	0.010	0.008
	(0.017)	(0.017)	(0.020)	(0.020)
Feel Other Students are Prejudiced	0.008	0.008	-0.054***	-0.054***
	(0.013)	(0.013)	(0.015)	(0.015)
Highest Parental Education	0.026***	0.024***	0.018**	0.016**
	(0.006)	(0.006)	(0.007)	(0.007)
Single Parent Household	-0.050	-0.051	-0.058	-0.059
	(0.041)	(0.041)	(0.048)	(0.047)
Number of Siblings in Home	-0.001	-0.001	0.005	0.004
	(0.012)	(0.012)	(0.014)	(0.014)
Female	0.186***	0.185***	0.086**	0.085**
	(0.031)	(0.031)	(0.036)	(0.036)
Hispanic	-0.033	-0.055	0.022	0.041
	(0.074)	(0.075)	(0.085)	(0.087)
Asian	0.044	0.025	-0.011	-0.005
	(0.085)	(0.087)	(0.099)	(0.100)
Black	0.011	0.014	-0.112	-0.102
	(0.092)	(0.096)	(0.106)	(0.110)
Spanish Spoken in Home	0.080	0.078	0.032	0.033
	(0.069)	(0.070)	(0.080)	(0.081)
Other Language Spoken in Home	0.071	0.053	-0.010	-0.013

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Table 4 – continued

	GPA		Attitudes	
	(SDM)	(GNS)	(SDM)	(GNS)
	β / SE	β / SE	β / SE	β / SE
	(0.076)	(0.077)	(0.088)	(0.089)
School Grade	0.026	0.036	0.053**	0.057**
	(0.023)	(0.024)	(0.027)	(0.027)
Peer Average of Parental Attitudes				
Two Parents in Low	-0.227**	-0.171*	-0.228**	-0.179*
	(0.091)	(0.090)	(0.105)	(0.108)
One Parent in Low	-0.044	-0.001	-0.197**	-0.186**
	(0.077)	(0.075)	(0.089)	(0.088)
One Parent in High	-0.134**	-0.127**	0.006	-0.016
	(0.062)	(0.060)	(0.072)	(0.072)
Two Parents in High	0.032	0.009	0.024	-0.016
	(0.067)	(0.065)	(0.077)	(0.079)
Peer Average of Controls				
Picture Vocabulary Test Scores	0.019	-0.015	0.030	0.031
	(0.023)	(0.023)	(0.026)	(0.026)
Feel Other Students are Prejudiced	-0.019	-0.021	-0.002	0.007
	(0.018)	(0.018)	(0.021)	(0.021)
Highest Parental Edu	0.004	-0.003	0.042***	0.037***
	(0.009)	(0.009)	(0.010)	(0.010)
Single Parent Household	0.060	0.052	0.104	0.101
	(0.057)	(0.056)	(0.066)	(0.065)
Peer Number of Siblings in Home	0.007	0.002	0.028	0.026
	(0.017)	(0.017)	(0.020)	(0.020)
Female	-0.049	-0.087**	-0.013	-0.019
	(0.044)	(0.042)	(0.050)	(0.050)
Hispanic	0.036	0.084	-0.033	-0.064
	(0.093)	(0.093)	(0.108)	(0.109)
Asian	0.081	0.066	0.026	0.002
	(0.099)	(0.099)	(0.114)	(0.115)
Black	-0.136	-0.098	0.100	0.085
	(0.102)	(0.105)	(0.119)	(0.121)
Spanish Spoken in Home	0.082	0.038	0.242**	0.218**
	(0.087)	(0.087)	(0.101)	(0.102)
Other Language Spoken in Home	0.174*	0.132	0.214*	0.193*
	(0.095)	(0.094)	(0.109)	(0.109)
School Grade	-0.028	-0.042	-0.058*	-0.063**
	(0.026)	(0.026)	(0.030)	(0.030)
Constant	1.490***	1.153***	-0.819***	-0.700***

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Table 4 – continued

	GPA		Attitudes	
	(SDM)	(GNS)	(SDM)	(GNS)
	β / SE	β / SE	β / SE	β / SE
	(0.249)	(0.216)	(0.286)	(0.267)
School Level FE	Yes	Yes	Yes	Yes
N	2174	2174	2174	2174
Likelihood	−2104.282	−2097.989	−2420.532	−2419.479

Note: * p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors in parentheses. SDM = Spatial Durbin Model, GNS = General Nesting Model

The endogenous effect in the GNS model for both GPA and attitudes is larger than in the SDM because of the negative estimates on the spatial correlation component. A negative spatial correlation suggests that omitting it from the model returns an estimate of the endogenous effect that is biased downward (per Lin (2015)). Lin (2010) finds a negative estimate of the correlation term in a GPA spatial model with the Add Health data. Lin (2015) finds the same result for spatial models studying peer effects over a variety of behaviors with the Add Health data. She comments in footnote 22 that such negative correlation implies negative selection on the dependent variable in friendship formation. This, she suggests, implies common tastes on the outcome of study is not driving friendship formation. Alternatively, as I discuss in chapter 4.3, this could relate to a case of distance between peers in terms of grades because of unobservables that once controlled for indicate the influence of peer grades is actually stronger.[2] Still, however, I recognize that peer group selection bias could remain a problem in the endogenous effect estimate, because I have not modeled the network formation. Estimating ρ provides a step towards reducing bias from the misspecified model that omits determinants of network formation that also influence the outcome.

2. I did explore omitting peer grades from the model but including the spatial error correlation. When I did this, I found a positive and significant value for ρ. This supports the idea that once we control for peer grades the correlation in the residuals is capturing variation from unobservables that create distance in grades.

Multiple own and contextual effects from the included covariates are significant. The presence of some significant contextual effects indicates that models omitting average peer variables for the covariates will miss these channels of peer effects, which can create spill-overs from changes in a variable in addition to the presence of the endogenous effect. Direct and indirect effects are explored in the partial effects.

The attitude models, in columns 3 and 4 of table 4, test the assumptions from the theory on the role of family and peer effects for the production of own-school attitudes (α_i). In both the SDM and GNS, the endogenous effect—or the impact from the weighted average attitudes of peers—on own-attitudes is positive and highly significant, indicating a social multiplier effect for attitudes about school. The magnitude of this effect ranges from 0.193 in the SDM model to 0.316 in the GNS model. Both models show that an adolescent's peers' attitudes influence their own attitudes. This is captured in the theory as an assumption. The evidence here is at least consistent with this assumption. Furthermore, this suggests there will be social effects in attitudes to the average individual in the school that will result in spill-overs for changes in attitudes across a school network.

With regards to peer group selection bias, the spatial correlation term is estimated to be negative, but it is only significant at the 10 percent level. Again, this indicates that after controlling for correllation in residuals between peers the effect from peer attitudes is stronger. When ρ is omitted the endogenous effect is biased downwards. If ρ fails to capture peer group selection effects, then the SDM estimate is at least free of the "reflection problem".

Own and contextual effects are present for multiple variable in the attitudes model. Among the own controls and peer average controls several are significant.[3] Again, direct and indirect effects for changes in explanatory variables are explored below.

3. The average of peer parental attitudes are the fraction of peers parents in each category of educational expecations.

6.1.1 Partial Effects of Schooling Attitudes Model

Table 5 reports the average impacts on school attitudes to the individual and across the network for changes in the independent variables using the results of the models reported in table 4. The direct, indirect, and total effects are average effects from a change in a variable. The indirect effects allow testing for the presence and strength of spatial spill-overs in each variable. Elhorst (2014) explains that in an OLS model the coefficients are the direct effects, or the effect of a change in x on the attitudes, but they do not include the feedback effects from the endogenous peer effect, while the spatial models do.[4]

The direct effects of parental college disappointment are as expected and highly significant. In the SDM, the estimated direct effects for these variables are -0.338 for two parents in the low and -0.223 for one parent in the low category both significant at the one percent level. Interpreting the SDM estimate, an average adolescent in the school network who experiences a change to the state of having two parents in the low college category is estimated to decrease schooling attitudes by 0.338 standard deviations.[5] This result combines the immediate impact on attitudes for the adolescent of the parental change and the return effects of changing peer attitudes in response to the individual's change in attitudes. For a change from the neutral category to the state of having two parents in the high college disappointment category (two parents in the high ideal indicator), interpreting the SDM estimate suggests a 0.251 standard deviation increase in own schooling attitudes at the one percent significance level. A similar interpretation can be made from the GNS model. These strong effects are consistent with expectations from the theory that family ideals influence attitudes about schooling.

The indirect effects estimate the average change over other network members' attitudes from a change in a variable for person *i*. In the GNS model, indirect effects are somewhat stronger,

4. Direct effect estimates are often very similar to the OLS coefficient estimates. It is the estimates for indirect effects that are especially important and use of coefficient estimates for spill-over interpretations risks erroneous inference.

5. Attitudes is standardized mean zero standard deviation of one but because of lost observations the standard deviation of attitudes for the sample is 0.833. I use the one standard deviation increase for interpretation as an approximate. More percisely the predicted change is 0.282 standard deviations.

but both models yield the same interpretations. The average effects are negative for parents in the low college disappointment categories and highly significant. This is consistent with the theoretical point that social spill-overs exist in family ideals. If families fall towards lower ideals their children's attitudes about school are impacted and this has a ripple effect in the network diminishing other adolescents' attitudes. A shift from the reference, or neutral category, to two parents in the low category has an estimated indirect effect of -0.360 in the SDM model and a change to the one parent low category has an estimated indirect effect of -0.295 standard deviations of schooling attitudes. Therefore, in a change for an average adolescent from the neutral category to either of these, the average cumulative effect to other adolescent's in the network is a strongly negative decrease in schooling attitudes. The high categories do not return significant estimates, indicating the spill-over effects work through changes to lower ideals. The results for the low categories are consistent with the theory around how peers and families influence own-attitudes such that spill-over effects can occur when families change their ideals.

Among the characteristic variables, the Add Health Picture Vocabulary Test, my ability proxy, is not estimated to have significant direct or indirect effects. Feeling that other students are prejudiced does have a significant direct effect estimate that is similar between the SDM and GNS. It implies that for the average adolescent in the school network greater levels of discrimination lowers schooling attitudes. The magnitude is not necessarily large, a standard deviation shift in feeling others are prejudiced is predicted to lower the average adolescent's schooling attitudes by 0.061 standard deviations.

Direct and indirect estimates for the highest number of years of parental education are positive and significant in both models. The direct effect estimate in the SDM predicts that adding one year of education increases attitudes by 0.018 standard deviations. The indirect effects are larger. These imply that increasing the highest parental education in the home for an average adolescent positively influences other members of the network. In the SDM, indirect effects predict that for every year of added education for an average adolescent, the cumulative change in schooling attitudes over the network is a 0.056 standard deviation increase. Thus, for example a shift of

four years, say from high school graduate to college graduate, predicts an average direct effect to an adolescent of 0.072 standard deviations and a spill-over effect of 0.224 standard deviations. Comparatively, these predictions are weaker than those found from the parental college disappointment indicators. Whether or not shifting family ideals on education is easier than shifting parental education, is for another study, but this does imply that the ideals a family transmits can impact an adolescents malleable attitudes about school and then spill-over from the adolescent through the school.

Of the remaining variables, estimates of the coefficients for the average direct effects on the female indicator and the school grade return significant results. Ethnicity and language spoken at home do not appear to have direct influences on schooling attitudes, although it could be there is simply not enough observations in each ethnicity to sufficiently capture the result. Females are estimated to have better attitudes about school than males and too those in higher grades. This school-grade effect is consistent with a maturation process or with those with worse attitudes dropping out of high school. School grade also is estimated to have a negative indirect effect. While I cannot conclude why this is the case, it is consistent with experiencing negative effects from friends in higher grades if older adolescent friends serve to provide access to negative behaviors such as drinking or smoking.

Speaking Spanish or any other language different from English in the home is not estimated to have direct effects, but both variables are estimated to have very strong spill-over effects in the school network. In both the SDM and GNS, these effects are around 0.30 standard deviations of schooling attitudes. It is not clear in the current framework what is driving these results. It may be that after controlling for ethnicity and discrimination the presence of those speaking different languages in the home builds a positive environment that motivates positive schooling attitudes in the network. No conclusion can be made here, but it especially suggests examining immigrants as a sub-group through the lens of identity may be worthwhile.

The total effects, in the third and sixth columns of table 5, show the combined direct and indirect effects. They capture both the influence to the average adolescent and the spill-overs cre-

ated in the network. One interpretation is that they represent the impact from changing a variable by the same amount across all other observations in the network on the outcome of one adolescent in the network (Lesage and Pace (2009)). Alternatively, it can be interpreted as the impact over all outcomes in the network, including the individual's, from changing a variable for just one individual. For example, the total effects from a shift to two parents in the low, or to just one parent, are quite large in both the SDM and GNS. These imply that changes to family ideals for a large enough portion of the network's families will have overall strong effects in the network for improving schooling attitudes, especially if a number of those were in the low category. In the SDM, a shift from two parents in the low to two parents in the high is predicted to result in an average total increase of 1.037 standard deviations in attitudes over the network, which is mirrored in the GNS model. Thus, changes in network members' family ideals can have large combined effects between the individual and the spill-over effects occurring through the school social space.

6.1.2 Spatial Partial Effects for GPA Model

Table 6 gives the results of the partial effects with GPA as the dependent variable for the preferred model, the GNS, and the SDM model for comparison.

In the GNS model, the average direct effect of increasing attitudes for the average network member is positive and significant, with a similar result in the SDM. For the average adolescent in a school, a standard deviation increase in schooling attitudes approximately increases GPA by 0.195 points, similar, and larger, to a standard deviation increase for the ability proxy.[6] Among the parental college disappoint variables only the one parent high category is significant at the five percent level. A change from the middle, reference, category to the one parent high is estimated to increase GPA by 0.09 points. Two parents in the high college disappointment category is positive as expected but only significant at the ten percent level. The one parent low category is significant at the ten percent level and estimated to reduce GPA by 0.099 points. These estimates are consis-

6. More precisely the direct effect in standard deviation terms is $0.195 * 0.833 = 0.162$.

tent with the transmission of family ideals playing a larger role through impact on the production of attitudes than through a conforming incentive.

Table 5. Partial Effects: Average Impact on School Attitudes to the Individual and Through the Network

	SDM			GNS		
	Direct (SE)	**Indirect** (SE)	**Total** (SE)	**Direct** (SE)	**Indirect** (SE)	**Total** (SE)
Two Parents in Low Category	-0.338***	-0.360***	-0.698***	-0.336***	-0.407**	-0.742***
	(0.077)	(0.133)	(0.162)	(0.079)	(0.161)	(0.186)
One Parent in Low Category	-0.223***	-0.295***	-0.519***	-0.218***	-0.365***	-0.584***
	(0.062)	(0.112)	(0.134)	(0.060)	(0.127)	(0.146)
One Parent in High Category	0.118**	0.034	0.151	0.117**	0.027	0.144
	(0.051)	(0.089)	(0.106)	(0.050)	(0.103)	(0.117)
Two Parents in High Category	0.251***	0.088	0.339***	0.253***	0.086	0.340**
	(0.054)	(0.096)	(0.116)	(0.056)	(0.118)	(0.134)
Picture Vocabulary Test Scores	0.010	0.040	0.049	0.008	0.049	0.056
	(0.020)	(0.032)	(0.037)	(0.020)	(0.035)	(0.040)
Feel Other Students are Prejudiced	-0.055***	-0.015	-0.070**	-0.056***	-0.014	-0.070**
	(0.015)	(0.025)	(0.030)	(0.015)	(0.031)	(0.034)
Highest Parental Education	0.018**	0.056***	0.074***	0.016**	0.061***	0.078***
	(0.007)	(0.012)	(0.015)	(0.007)	(0.015)	(0.017)
Single Parent Household	-0.058	0.116	0.058	-0.060	0.122	0.062
	(0.048)	(0.084)	(0.102)	(0.046)	(0.100)	(0.115)
Number of Siblings in the House	0.005	0.036	0.041	0.004	0.040	0.044
	(0.014)	(0.025)	(0.029)	(0.014)	(0.027)	(0.031)
Female	0.087**	0.004	0.091	0.087**	0.009	0.096
	(0.037)	(0.059)	(0.058)	(0.037)	(0.064)	(0.061)
Hispanic	0.022	-0.036	-0.013	0.042	-0.075	-0.033
	(0.086)	(0.129)	(0.147)	(0.089)	(0.140)	(0.149)
Asian	-0.011	0.030	0.018	-0.006	0.001	-0.005
	(0.100)	(0.128)	(0.136)	(0.102)	(0.143)	(0.147)
Black	-0.113	0.098	-0.015	-0.105	0.080	-0.025
	(0.104)	(0.132)	(0.123)	(0.108)	(0.147)	(0.131)
Spanish Spoken in the Home	0.032	0.307**	0.340**	0.033	0.333**	0.366**
	(0.080)	(0.120)	(0.135)	(0.083)	(0.137)	(0.147)
Other Language Spoken in the Home	-0.010	0.263**	0.252*	-0.013	0.277*	0.264*
	(0.085)	(0.134)	(0.148)	(0.089)	(0.150)	(0.157)
School Grade	0.054*	-0.060*	-0.006	0.058**	-0.067**	-0.009
	(0.027)	(0.032)	(0.022)	(0.026)	(0.034)	(0.023)

Note: * p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors are in parentheses. Standard errors are drawn from a simulation based on $Pv + [\hat{\theta}']$ where P is the lower triangular Cholesky decomposition of the estimated variance-covariance (VCV) matrix and and $\hat{\theta}$ is the estimated parameters. The simulation takes 1,000 draws of v a vector with length equal to the number of parameters drawn normal mean zero and standard deviation of one (see Elhorst (2014) chapter 2 for more details).

Table 6. Partial Effects: Average Impact on GPA to the Individual and Through the Network

	SDM			GNS		
	Direct (SE)	**Indirect** (SE)	**Total** (SE)	**Direct** (SE)	**Indirect** (SE)	**Total** (SE)
Attitudes	0.208***	0.061***	0.270***	0.195***	0.137***	0.333***
	(0.018)	(0.005)	(0.023)	(0.020)	(0.014)	(0.033)
Two Parents in Low Category	-0.004	-0.298**	-0.303**	-0.007	-0.311**	-0.318*
	(0.070)	(0.120)	(0.148)	(0.070)	(0.154)	(0.172)
One Parent in Low Category	-0.091*	-0.085	-0.175	-0.099*	-0.071	-0.170
	(0.053)	(0.099)	(0.117)	(0.051)	(0.129)	(0.141)
One Parent in High Category	0.084*	-0.151*	-0.067	0.090**	-0.164	-0.073
	(0.045)	(0.081)	(0.097)	(0.043)	(0.103)	(0.112)
Two Parents in High Category	0.085*	0.067	0.153	0.083*	0.075	0.158
	(0.049)	(0.088)	(0.107)	(0.048)	(0.111)	(0.124)
Picture Vocabulary Test Scores	0.142***	0.067**	0.209***	0.144***	0.075**	0.219***
	(0.018)	(0.029)	(0.034)	(0.018)	(0.037)	(0.041)
Feel Other Students are Prejudiced	0.008	-0.023	-0.015	0.008	-0.031	-0.023
	(0.013)	(0.025)	(0.029)	(0.013)	(0.030)	(0.033)
Highest Parental Education	0.026***	0.012	0.038***	0.026***	0.013	0.039**
	(0.006)	(0.011)	(0.013)	(0.006)	(0.014)	(0.016)
Single Parent Household	-0.051	0.064	0.013	-0.053	0.055	0.002
	(0.042)	(0.075)	(0.093)	(0.041)	(0.096)	(0.107)
Number of Siblings in the Home	-0.001	0.008	0.007	-0.001	0.002	0.001
	(0.012)	(0.022)	(0.026)	(0.013)	(0.028)	(0.031)
Female	0.189***	-0.008	0.180***	0.194***	-0.019	0.175***
	(0.032)	(0.053)	(0.053)	(0.033)	(0.064)	(0.061)
Hispanic	-0.033	0.038	0.004	-0.058	0.109	0.052
	(0.074)	(0.114)	(0.130)	(0.078)	(0.140)	(0.144)
Asian	0.044	0.120	0.164	0.026	0.136	0.162
	(0.087)	(0.116)	(0.123)	(0.093)	(0.144)	(0.142)
Black	0.012	-0.174	-0.163	0.015	-0.165	-0.150
	(0.091)	(0.115)	(0.114)	(0.100)	(0.142)	(0.127)
Spanish Spoken in the Home	0.081	0.131	0.212*	0.082	0.125	0.206
	(0.072)	(0.115)	(0.127)	(0.071)	(0.134)	(0.141)
Other Language Spoken in the Home	0.072	0.250**	0.322**	0.056	0.276*	0.332**
	(0.078)	(0.120)	(0.138)	(0.077)	(0.147)	(0.154)
School Grade	0.026	-0.028	-0.002	0.037	-0.048	-0.011
	(0.024)	(0.029)	(0.019)	(0.025)	(0.032)	(0.022)

Note: * p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors are in parentheses. Standard errors are drawn from a simulation as noted in the previous table.

The ability proxy, parental education, and being female have significant direct effects on GPA. The Add Health Picture Vocabulary test scores are positive and significant, as one may expect of an ability proxy with relation to GPA. In the GNS, the average direct effect for the ability proxy is 0.15. Comparing this to the average direct effect on the attitudes index implies that a standard deviation change in attitudes leads to a slightly larger impact on GPA, as a standard deviation increase in the Add Health Picture Vocabulary test scores. The highest parental education

level positively effects GPA, which may result from an improved ability to support the children's educational needs or simply through access to more resources if education returns greater wages. A standard deviation shift in the highest parental education in the home predicts a small 0.07 GPA point increase. Thus, an implication combined with the results for the average direct effects of the parental ideal proxies is that families affect performance more through their influence on adolescent attitudes than directly onto performance. Finally, the direct effect estimate for females indicates that the average adolescent female in a school scores 0.194 GPA points higher than the average male.

Evidence for indirect effects from changes in schooling attitudes is strong. It is positive and significant at the one percent level in both the SDM and the GNS, though stronger in magnitude in the GNS. For the GNS, a one standard deviation increase in schooling attitudes is estimated to return an average cumulative increase for other adolescent's in the network of 0.137 GPA points. In the attitudes model, the evidence supported endogenous peer effects in schooling attitudes that cause changes in attitudes to impact adolescent attitudes over the network. Here we see own-attitudes impact GPA and that changes in own-attitudes spill-over to create positive changes in GPA over the network. Therefore, schooling attitudes spread over the network and impact GPA, and changes in attitudes create further improvements in performance for the adolescent and others in the network.

Indirect effects among the family ideal variables are only found to be strong for the two parents in the low college disappointment category. The estimate is significant at the five percent level in both the SDM and the GNS. Interpreting the GNS estimate, a discrete change for the average adolescent from having parents in the neutral category to two parents in the low category results in an average cumulative reduction of GPA to other adolescent's in the network of 0.311 points. The one parent in the high ideal category has a non-intuitive, negative indirect effect estimate that is significant in the SDM at the 10 percent level and not significant in the GNS. The two parent high category is not significant, though the point estimate for the indirect effect is positive, as expected. Why the one parent with a high ideal category results in a negative indirect ef-

fect is not entirely clear. It may be that the result is simply a bad draw. Alternatively, if we take it as negative, then it implies that a change from the neutral category to the one parent in the high category has a negative impact on the adolescent's friends GPA. Overall, and sticking with the GNS model, the parental ideal variables indicate spill-overs occur if two parents have low educational ideals. Also, recall that the indirect effect is an average of the cumulative spill-overs across the school. It can be bigger than the direct effect. This implies that there is a direct effect, though small, that results in spill-overs showing up when we aggregate all the spillovers in the network into an average effect.

The indirect effect estimates for the ability proxy is significant but not so for the highest parental education in the home. Comparing these results to the attitudes model points to family inputs largely working through their influence on own-attitudes. The picture vocabulary test score has an indirect effect in the GNS model of 0.082 GPA points for a standard deviation increase in the test score significant at the five percent level. Comparing the indirect effects of the ability proxy and attitudes indicates that a standard deviation change in either results in relatively similar impacts on GPA. Of the other variables, only the Spanish spoken in the home indicator returns estimates of significant indirect effects on GPA. The estimated effect is positive but marginally significant. Nevertheless it furthers the finding of positive indirect effects on attitudes from Spanish spoken in the home and suggests exploring peer effects in relationship to immigrants is an interesting extension.

The total effect from a change in attitudes is highly significant. It shows that the combined overall average increase in GPA for a standard deviation increase in the attitudes of an average adolescent in the school and others around her is 0.333 GPA points (using the GNS model). This is slightly larger than the total effect for a standard deviation increase in vocabulary test scores, implying that positively shifting ideals around schooling results in similar overall improvements in performance as does positively shifting ability.

6.2 Robustness and Extended Analyses

To parse out the models further, I explore robustness checks and extensions. First, I use the peers of peers characteristics as instruments for the endogenous peer effect in case controlling for the spatial correlation term (ρ) failed to capture variation from omitted variables due to the peer group selection process, leaving selection effects to persist. Second, I explore the effect of attitudes on performance in a later period. Third, I use an alternative dependent variable, final educational attainment, a long-term measure of effort. Finally, I explore some additional sensitivity checks for the model results. One, briefly considers an alternative to the parental college disappointment for the parental effect on attitudes and performance, and the second makes use of a friendship reciprocity assumption to gain back observations lost when using the directed graph.

6.2.1 Peers of Peers as Instruments

With network data, peers of peers are two links away and theoretically only influence the individual through their influence on the individual's one link away peers. Bramoullé, Djebbari, and Fortin (2009) lay the theoretical groundwork for using these as instruments for the endogenous effect. Econometrically the implementation of peers of peers as instruments has a corollary in the spatial econometrics literature, where regions that are indirectly linked have been suggested as instruments for the endogenous effect (Kelejian and Prucha 1998; Lee 2003; Kelejian and Prucha 2010).[7]

Table 7 reports the instrumental variable (IV) model results from using peers of peers as instruments for the endogenous peer effect. The IVs from peers of peers do not include the outcome, rather the background characteristics. The outcome cannot be used because it is a part of

7. Lee (2003) establishes, under certain regularity conditions, the best generalized spatial two stage least squares estimator that is asymptotically efficient compared to other estimators in the class. His approach involves first estimating the instrumental variables (IV) model with the neighbor of neighbor characteristics and then using the reduced form prediction from that estimation to create an average of the predicted neighbor lags in the dependent variable ($W\hat{y}$). In the second step, $W\hat{y}$ is used as an instrument for the endogenous variable Wy. I do not present this extra step, because, while I want to compare the point estimates from using the peers of peers as instruments to my previous results, I also want to focus on the relevance of peers of peers as instruments. This second goal concentrates the attention to the peers of peers IV step, rather than the asymptotically efficient extension with Lee's method. Thus, for conciseness I keep the results in table 5 to those of interest.

the global chain of actions and reactions and is endogneous to the average of peer outcomes (the first stage).

For the attitudes model in column 1, the estimated endogenous effect is about 0.277 points larger than its estimate for the SDM results reported in table 2 and 0.15 points larger than its estimate for the GNS model. It remains highly significant and continues to indicate that spill-overs in attitudes occur over a school social space. For the GPA model in table 7, the estimated endogenous effect is about 0.11 points larger than its estimate in the SDM results reported in table 4, while it is about 0.10 points smaller than its estimate in the GNS model. It too remains highly significant and continues to indicate that spill-overs in GPA occur over a school social space. The overall results remain consistent.

Table 7. Peers of Peers as IVs for the Endogenous Effect

	Attitudes β / SE	GPA β / SE
Endogenous Effect	0.470*** (0.169)	0.343*** (0.108)
N	2174	2174
Hansen J (p-value)	0.082	0.410
Montiel-Pflueger "Effective" F	3.019	6.108
Montiel-Pflueger Critical (tau=5%)	24.038	24.108
Montiel-Pflueger Critical (tau=30%)	6.090	6.116

Note: Robust standard errors are in parentheses. Models are estimated with the same set of variables as in table 2—to include school fixed effects—but with peers of peers characteristics as instruments rather than estimating the spatial correlation term.

A concern, however, with using peers of peers as instruments is that these second order neighbors may yield weak instruments and be sensitive to model specification (Lee, Liu, and Lin 2010; Lesage and Pace 2009). The p-value from the Hansen J statistic fails to reject the null at the five percent level (though not the ten percent) in the attitudes model, and in the GPA model it is far from rejecting the null, returning a p-value of 0.410. These provide some evidence that the overidentification restrictions are met. The instruments may still be weak. Montiel and Pflueger (2013) provide a weak instrument test that extends the Stock-Yogo test from Stock and Yogo

(2005) and is robust to heteroscedasticity, serial correlation, and clustering.[8] Their "effective" F statistic is reported in table 7, with comparable critical values based on levels of acceptable bias (τ). Notably, in both models the test statistic falls well below the critical values for the five percent worst case acceptable bias, implying we cannot reject the null of weak instruments. In fact, even moving to the thirty percent worst case acceptable bias continues to result in failing to reject the null. Therefore, this instrumenting strategy may result in poor performance and I continue to select the results of table 4 as the preferred results.

6.2.2 Checking the Effect of Attitudes

Unobserved heterogeneity resulting from simultaneity between current period attitudes and current period GPA is a threat to the identification of attitudes effect on performance. I use Add Health data from wave II and instrument current period attitudes in wave II with own and peer attitudes from wave I for the GPA model. For the saturated school sample, Add Health recollected friendship nominations in wave II.[9] Wave II took place approximately one year after wave I and covered the 1995-1996 school year. The sample size falls to $1,400$ observations after listwise deletion of missing observations and constructing the directed graph for wave II peer networks. I include the same set of covariates as in the main results of table 4. Time varying variables are drawn from wave II responses. Additionally, the individual level time lags for GPA and attitudes and peer average time lags for GPA and attitudes are included in some specifications of table 8. Overall, table 8 shows a consistent story in which attitudes about school impact performance.

Time lagged attitude instruments can serve as appropriate instruments only if their influence on wave II GPA entirely runs through their impact on wave II attitudes and the errors are not serially correlated. Controlling for lag GPA may bias its coefficient estimate up and other model coefficients down if there is serial autocorrelation between periods (Bond 2002). Own and peer

8. Implemented in Stata with the user written package *weakivtest*.

9. Studying peer effects more specifically through the dynamics in peer groups is an interesting question for future research. See Patachini, Rainone, and Zenou (2016) for a recent paper that explores such a question by studying the impact of short term versus long term peers on later life educational attainment.

attitudes in the first period may influence first period GPA, shaking an individual's confidence or simply impacting the level of knowledge they have to draw from in the next school year. By controlling for wave I GPA this channel of time lagged attitude impacts on wave II GPA is controlled out; however, it may also create other problems if the time period error terms are correlated. Add Health does not contain a third wave for the high school period, thus a fully dynamic panel data model cannot be explored to remove the bias in lagged GPA. Alternatively, I also consider in column 4 the spatial model for wave II with lagged attitudes and lagged peer attitudes but no current period attitudes nor lagged GPA. In this case, the estimate on lagged attitudes avoids simultaneity because of the timing, but serial autocorrelation may still yield the estimates unreliable.

Column 1 reports estimates for the wave II equivalent specification to the SDM results for wave I with GPA as the dependent variable.[10] The parameter estimate for own-attitudes is very similar to the wave I estimate. The effect of current period attitudes decreases when including time lagged GPA—seen in columns 2 and 3—but remains significant at the one percent level. The specifications in columns 3 including time lagged GPA and time lagged own and peer attitudes should return an approximately zero effect for the lagged attitude variables, if they indeed form good instruments when controlling for lagged GPA. The results show evidence consistent with this point. In column 4, omitting lagged GPA and current period attitudes but including lagged attitudes returns a strongly positive estimate for the effect of lagged attitudes on GPA close to the estimate for current period attitudes in column 1. Lagged attitudes is free of problems from simultaneity, and if it is free from problems of serial autocorrelation, then the estimates in column 4 provide a good indication that attitudes have a true effect on performance. This must be interpreted with caution because I cannot rule out correlated heterogeneity between time periods.

Columns 5 and 6 report the results from using time lagged own and peer attitudes as instruments for wave II own attitudes where both specifications include the full set of model family, peer, control, and school fixed effect variables. Both IV specifications pass the overidentification test. Also, neither fail the weak instruments test. Column 5 includes time lagged GPA as a con-

10. The ρ term was negative but not significant in the wave II models, so I focus on the SDM for table 8.

trol. The effect of attitudes is estimated to be positive and almost identical to its effect in column 2, when including time lagged GPA in the spatial model with no instruments. In column 6, when dropping lagged GPA but keeping all controls, peer variables, and school fixed effects the estimated effect of current period attitudes rises sharply. Thus, if lagged GPA is biased upwards and attitudes biased down from autocorrelation between time periods then the specifications including it underestimate the impact of attitudes. The results in column 6, when omitting lagged GPA as a control, may violate the exclusion restrictions (no evidence in the test statistics) or also suffer from autocorrelation as well. At any rate, the story throughout table 6 is consistent. Attitudes continue to be estimated with a positive and significant effect on GPA.[11]

Table 8. Period 2 GPA Models Including Period 1 and 2 Attitudes and Period 1 GPA

	SDM ML				IV	
	(1)	(2)	(3)	(4)	(5)	(6)
Attitudes (95-96)	0.214***	0.133***	0.135***		0.126***	0.280***
	(0.021)	(0.018)	(0.022)		(0.037)	(0.038)
Lagged GPA (94-95)		0.494***	0.494***		0.492***	
		(0.023)	(0.023)		(0.025)	
Lagged Attitudes (94-95)			-0.007	0.170***		
			(0.024)	(0.023)		
Lagged Peer Attitudes (94-95)			0.012	0.052		
			(0.028)	(0.032)		
Peer GPA (95-96)	0.169***	0.114***	0.112***	0.170***	0.147***	0.219***
	(0.028)	(0.026)	(0.026)	(0.029)	(0.030)	(0.033)
N	1400	1400	1400	1400	1400	1400
Likelihood	-1271.346	-1072.629	-1072.504	-1292.236		
Hansen J (p-value)					0.823	0.956
Montiel-Pflueger "Effective" F					268.129	304.652
Montiel-Pflueger Critical (tau=5%)					6.017	7.213

Note: * p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors are in parentheses. Standard errors of IV models are robust to heteroskedasticity. Models 1-4 are the Spatial Durbin Model (SDM) estimated by maximum likelihood. Models 5-6 are instrumental variable models using period 1 own-attitudes and period 1 peer attitudes as instruments for period 2 attitudes. All models are estimated with the set of key parental variables, controls, peer average variables, and school fixed effects corresponding to those of the main GPA model specification.

11. I checked the IV results using the Add Health grand sample survey weights for wave 2 stratified by region. The key results were unchanged, with results for wave II own-attitudes, wave I GPA, and peer GPA almost exactly the same.

6.2.3 Years of Educational Attainment

As another check for the effect of attitudes on education, I draw final years of education from Add Health's fourth wave, when the respondents are in their late twenties or early thirties. All covariates are the same as in the main analysis of table 4 and drawn from wave I. Table 9 reports the results for three specifications. The first estimates a spatial model including own and peer attitudes but excluding own and peer GPA. In this case, own-attitudes is estimated to have a positive and strongly significant direct effect on years of education. Moreover, own-attitudes have positive and spill-over effects as well, though they are less precisely estimated. Specification 2 includes both own and peer GPA in the GNS model. In this case, the spatial correlation term is negative but not significant and the coefficient on average peer years of education is less precisely estimated than it is in specification 3, which omits the spatial correlation term.

Table 9. Impact of Attitudes on Years of Educational Attainment

	(1) GPA Excluded			(2)	(3) GPA Included		
	β / SE	Direct	Indirect	β / SE	β / SE	Direct	Indirect
Peer Years of Educ	0.321***			0.205**	0.063**		
	(0.064)			(0.087)	(0.027)		
ρ	-0.215***			-0.151			
	(0.071)			(0.093)			
Attitudes	0.403***	0.414***	0.208*	0.232***	0.240***	0.240***	0.016***
	(0.055)	(0.056)	(0.113)	(0.051)	(0.052)	(0.051)	(0.003)
GPA				0.765***	0.777***	0.778***	0.328***
				(0.060)	(0.060)	(0.059)	(0.081)
Peer GPA	No			Yes	Yes		
Peer Attitudes	Yes			No	No		
Parental Attitudes	Yes			Yes	Yes		
Controls	Yes			Yes	Yes		
Peer Parental Attitudes	Yes			Yes	Yes		
Peer Controls	Yes			Yes	Yes		
School Level FE	Yes			Yes	Yes		
N	1594			1594	1594		
Likelihood	−2966.451			−2871.567	−2872.245		

Note: * p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors are in parentheses. Specification (1) and (3) report model coefficients, direct effects, and indirect effects side by side. Standard errors for the direct and indirect effects are drawn as before.

In specification 3, own-attitudes still has a direct effect that is highly significant even with GPA in the model. Thus attitudes about school impact educational attainment implying spill-overs in attitudes within a school—which the estimated effect of peer attitudes on own-attitudes in table 4 indicates exist—will have later direct effects on years of education. Direct effects and spill-overs from changes in GPA are estimated to be present and large. Overall, attitudes impacts final years of education even controlling for GPA. Any effects of attitudes on GPA will only magnify the effect of attitudes on the years of educational attainment.

6.2.4 An Alternative to College Expectations: Parental Involvement

Here I explore an alternative measure for the family ideals on education. I use parental communication with the adolescent about school as an alternative measure to the college disappointment indicators that captures family involvement with the adolescent on school matters. This variable is constructed from survey questions asking the respondent whether they have talked with their mother and father about school work or grades and talked about things they are doing in school in the last four weeks. The variable is a count of each "yes" response across four questions (two about interactions with the mother and two about the father) that ranges from zero to four. Family involvement may not be entirely the same as the ideals. It may also relate to the time the family has to be involved or potentially be simultaneously determined with student performance, whereas I have argued the ideals are likely to remain unaffected by current period performance. Thus, family norms about educational effort may impact their involvement (especially if the parents' themselves gain identity utility from being involved or not), but involvement may also relate to other factors implying it is likely endogenous. It is for this argument that I use parental college disappointment as my preferred measure of the ideals transmitted making up the family educational norm. Nevertheless, considering family involvement provides an alternative measure that has also been explored previously in the literature.

The endogeniety of family involvement to children's education has been pointed out previously, but because of data limitations it has only been in the relatively recent past that economist

have paid any attention to the matter.[12] Those studies which have explored family involvement have found much stronger and consistent effects on non-cognitive outcomes (Avvisati, Besbas, and Guyon 2011). Although, Cabus and Ariës (2016) have found strong causal effects of family involvement on test scores with an instrumenting strategy, and Avvisati et al. (2014) also found some positive results on test scores in addition to strong effects on behavioral outcomes from increases in family involvement in a field experiment. Thus, I expect family involvement to have a positive effect on student attitudes and a small positive effect on GPA. In both cases, a downward bias in the coefficient estimates for family involvement is expected based on the literature regarding the matter. Moreover, if family involvement captures more than family ideals, then estimates should be relatively unchanged when including both the college disappointment indicators and the involvement variable. The model results reported in table 10 and the partial effects reported in table 11 support these points.

In table 10, the GNS spatial model results for own-attitudes and GPA are reported including the count of parental involvement. Columns 1 and 3 omit the parental college expectations and include parental involvement and columns 2 and 4 include them with parental involvement. The peer endogenous effect remains positive and significant for both attitudes and GPA and are similar to their previous estimates in table 4.

12. See Avvisati, Besbas, and Guyon (2011) for a review article.

Table 10. An Alternative to Parental College Disappointment: Parental Communication about School

	Attitudes		GPA	
	β / SE	β / SE	β / SE	β / SE
Count of Parental/Respondent School Interactions				
Own Parental Interactions	0.066***	0.052***	0.025**	0.021**
	(0.012)	(0.012)	(0.010)	(0.010)
Peer Parental Interactions	0.021	0.017	-0.015	-0.015
	(0.017)	(0.016)	(0.014)	(0.014)
Parental College Disappointment Categories				
Two Parents in Low		-0.319***		-0.005
		(0.076)		(0.066)
One Parent in Low		-0.195***		-0.088*
		(0.059)		(0.051)
One Parent in High		0.114**		0.087**
		(0.049)		(0.042)
Two Parents in High		0.237***		0.075
		(0.054)		(0.047)
Peer Two Parents in Low		-0.165		-0.168*
		(0.107)		(0.090)
Peer One Parent in Low		-0.168*		-0.005
		(0.088)		(0.075)
Peer One Parent in High		-0.011		-0.128**
		(0.072)		(0.060)
Peer Two Parents in High		-0.017		0.009
		(0.078)		(0.065)
Attitudes			0.196***	0.183***
			(0.017)	(0.018)
Peer D.V. (Endogenous Effect)	0.323***	0.311***	0.461***	0.447***
	(0.069)	(0.067)	(0.037)	(0.040)
ρ	-0.124	-0.141*	-0.275***	-0.257***
	(0.079)	(0.076)	(0.047)	(0.050)
Controls	Yes	Yes	Yes	Yes
Peer Average Variables	Yes	Yes	Yes	Yes
School Level FE	Yes	Yes	Yes	Yes
N	2174	2174	2174	2174
Likelihood	−2466.752	−2407.852	−2107.870	−2095.533

Note: * p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors are in parentheses.

Columns 1-4 of table 11 report the direct and indirect effects of the attitudes model and columns 5-8 of the GPA model.[13] For both dependent variables, family involvement is included without and then with the family college disappointment indicators. In column 1, omitting college disappointment indicators, family involvement is estimated to have a positive and significant direct effect and indirect effect on attitudes, but these estimates are likely biased. Adding back the college disappointment indicators in column 2 returns a similar result for the family involvement

13. Total effects are omitted for space.

effects and the partial effect estimates for the disappointment indicators remain almost unchanged from their estimates in table 5 of this chapter.

For GPA as the dependent variable, whether omitting the college disappointment indicators or not the direct effects are significant and positive but small, while indirect effects are insignificant and close to zero. Again, this is consistent with expectations based upon past research on the effect of family involvement. Including the parental college disappointment indicators returns estimates for their direct and indirect effects consistent with their estimates in table 6.

Table 11. Partial Effects with Parental Communication and Help with School Projects as an Alternative to College Disappointment

	Attitudes				GPA			
	Direct (SE)	**Indirect** (SE)	**Direct** (SE)	**Indirect** (SE)	**Direct** (SE)	**Indirect** (SE)	**Direct** (SE)	**Indirect** (SE)
Family Involvement	0.068*** (0.012)	0.061** (0.025)	0.053*** (0.012)	0.047* (0.024)	0.026** (0.011)	-0.008 (0.024)	0.022** (0.010)	-0.012 (0.024)
Two Parents in Low			-0.326*** (0.076)	-0.377** (0.152)			-0.005 (0.068)	-0.307* (0.161)
One Parent in Low			-0.200*** (0.061)	-0.328** (0.130)			-0.093* (0.053)	-0.076 (0.130)
One Parent in High			0.117** (0.050)	0.032 (0.104)			0.091** (0.045)	-0.165 (0.104)
Two Parents in High			0.242*** (0.054)	0.076 (0.116)			0.079* (0.049)	0.073 (0.115)
Controls	Yes		Yes		Yes		Yes	
Peer Average Variables	Yes		Yes		Yes		Yes	
School Level FE	Yes		Yes		Yes		Yes	
N	2174		2174		2174		2174	

Note: * p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors are in parentheses and drawn by simulation, as discussed previously.

Overall, it appears excluding or including family involvement does not affect the results for college disappointment as a measure of family ideals. Additionally, family involvement is found to have larger effects on attitudes about school than on performance in school. Given the literature on family involvement, and specifically the results of Avvisati et al. (2014) and Cabus and Ariës (2016), it is likely the effect of family involvement is underestimated. Therefore, whether based upon college disappointment as a measure of family ideals or family involvement, families

matter and changes can spill effects over school networks. Caution is still in order with respect to conclusions on causality. I contend that the evidence here shows how family and peer effects are intertwined, implying changes in family ideals and attitudes can have strong effects because they influence not only the adolescent but others linked in a school social space.

6.2.5 Alternative Weight Matrix

The undirected graph, based on an assumption of friendship reciprocity, is used as a check against bias from missing data. When constructing the spatial weights matrix with friendship nominations defining the peer links, those with all missing friendship nominations are omitted from the data. To recover a number of these observations, I consider an assumption of friendship reciprocity, thus if person i names person j as their friend but j does not name i person j will still receive a link for person i. The sample size for the analysis is now $2,725$. Only those who name nobody and are named by nobody are omitted because of missing friendship nominations with the undirected graph (approximately 300 respondents). It must be noted that the reciprocity assumption increases the size of each adolescent's peer group and may induce links where they do not exist. One would expect this to result in a reduction of model fit.

Model results using the undirected graph are reported in tables 12 and 13. The undirected graph is formed from the friendship nominations and the friendship reciprocity assumption. Endogenous effect estimates in table 12 are very similar to their estimates with the directed graph but for the GNS attitudes model. The endogenous peer effect in this case is much higher as a result of the more strongly negative estimate of the spatial correlation component ρ. The likelihood values for the undirected graph models do fall compared to those in table 4, which is consistent with the expectation that the reciprocity assumption will result in a poorer model fit of the data.

Table 12. Spatial Models for GPA and Attitudes (W_2)

	GPA		Attitudes	
	(SDM)	(GNS)	(SDM)	(GNS)
	β / SE	β / SE	β / SE	β / SE
Endogenous Effect	0.251***	0.488***	0.174***	0.506***
	(0.021)	(0.041)	(0.023)	(0.037)
ρ		-0.293***		-0.386***
		(0.051)		(0.045)
Attitudes	0.194***	0.173***		
	(0.016)	(0.016)		
Parental Attitudes on College				
Two Parents in Low	-0.034	-0.027	-0.341***	-0.320***
	(0.058)	(0.058)	(0.069)	(0.069)
One Parent in Low	-0.063	-0.062	-0.161***	-0.137**
	(0.046)	(0.046)	(0.054)	(0.054)
One Parent in High	0.079**	0.080**	0.125***	0.096**
	(0.038)	(0.038)	(0.045)	(0.045)
Two Parents in High	0.104**	0.101**	0.261***	0.236***
	(0.042)	(0.042)	(0.050)	(0.050)
Controls				
Picture Vocabulary Test Scores	0.147***	0.139***	0.012	0.001
	(0.015)	(0.016)	(0.018)	(0.019)
Feel Other Students are Prejudiced	0.015	0.013	-0.063***	-0.065***
	(0.011)	(0.011)	(0.013)	(0.013)
Highest Parental Edu	0.027***	0.024***	0.010	0.004
	(0.006)	(0.006)	(0.007)	(0.007)
Single Parent Household	-0.017	-0.017	-0.073*	-0.077*
	(0.036)	(0.036)	(0.043)	(0.043)
Number of Siblings in Home	0.008	0.005	0.005	0.002
	(0.011)	(0.011)	(0.013)	(0.013)
Female	0.198***	0.199***	0.072**	0.079**
	(0.027)	(0.027)	(0.032)	(0.033)
Hispanic	-0.075	-0.069	0.085	0.105
	(0.067)	(0.069)	(0.080)	(0.083)
Asian	-0.012	-0.014	0.092	0.061
	(0.081)	(0.085)	(0.096)	(0.102)
Black	0.099	0.115	0.049	0.057
	(0.082)	(0.088)	(0.097)	(0.106)
Spanish Spoken in Home	0.147**	0.123**	0.022	-0.002
	(0.060)	(0.061)	(0.071)	(0.073)
Other Language Spoken in Home	0.095	0.059	-0.014	-0.050

Continued on next page

Table 12 – continued

	GPA		Attitudes	
	(SDM)	(GNS)	(SDM)	(GNS)
	β / SE	β / SE	β / SE	β / SE
	(0.071)	(0.073)	(0.084)	(0.087)
School Grade	0.034*	0.048**	0.032	0.039
	(0.021)	(0.022)	(0.024)	(0.026)
Peer Average of Parental Attitudes				
Two Parents in Low	-0.134	-0.102	-0.134	-0.008
	(0.094)	(0.091)	(0.111)	(0.108)
One Parent in Low	0.012	0.033	-0.188**	-0.122
	(0.080)	(0.077)	(0.095)	(0.091)
One Parent in High	-0.100	-0.121*	0.111	0.084
	(0.066)	(0.064)	(0.078)	(0.075)
Two Parents in High	0.027	-0.022	0.105	0.018
	(0.070)	(0.068)	(0.083)	(0.081)
Peer Average of Controls				
Picture Vocabulary Test Scores	0.026	-0.017	0.033	0.031
	(0.023)	(0.024)	(0.027)	(0.027)
Feel Other Students are Prejudiced	-0.020	-0.019	0.023	0.044**
	(0.018)	(0.018)	(0.022)	(0.021)
Highest Parental Edu	0.010	0.004	0.045***	0.037***
	(0.009)	(0.009)	(0.011)	(0.010)
Single Parent Household	0.044	0.042	0.107	0.117*
	(0.061)	(0.059)	(0.072)	(0.069)
Peer Number of Siblings in Home	0.025	0.025	0.018	0.019
	(0.017)	(0.017)	(0.020)	(0.020)
Female	-0.026	-0.079*	0.010	-0.033
	(0.042)	(0.043)	(0.050)	(0.050)
Hispanic	-0.032	-0.011	-0.036	-0.082
	(0.097)	(0.096)	(0.116)	(0.114)
Asian	0.049	0.010	0.031	-0.012
	(0.106)	(0.106)	(0.125)	(0.127)
Black	-0.211**	-0.200*	0.001	-0.037
	(0.102)	(0.105)	(0.121)	(0.126)
Spanish Spoken in Home	0.155*	0.104	0.268**	0.225**
	(0.089)	(0.089)	(0.106)	(0.105)
Other Language Spoken in Home	0.199*	0.153	0.267**	0.228*
	(0.103)	(0.100)	(0.122)	(0.117)
School Grade	-0.033	-0.052**	-0.039	-0.048
	(0.024)	(0.025)	(0.028)	(0.029)
Constant	1.239***	0.864***	-0.941***	-0.673***

Continued on next page

Table 12 – continued

	GPA		Attitudes	
	(SDM)	(GNS)	(SDM)	(GNS)
	β / SE	β / SE	β / SE	β / SE
	(0.239)	(0.200)	(0.282)	(0.214)
School Level FE	Yes	Yes	Yes	Yes
N	2725	2725	2725	2725
Likelihood	−2635.741	−2626.875	−3088.194	−3073.001

Note: * p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors in parentheses. SDM = Spatial Durbin Model, GNS = General Nesting Model

Table 13 provides the partial effects for the undirected graph for both the attitudes and GPA models. Only the GNS results are reported for conciseness and because the GNS returns the best fit of the data in both cases. Again none of the overall conclusions change. There are some changes in significance to the parental college disappointment indicators. In the attitudes model, the indirect effect for two parents in the low category is no longer significant—though the point estimate remains negative and large—and the one parent low category continues to be significant at the 5 percent level. Furthermore, indirect effects for the one parent high and two parent high categories are now significant at the 10 percent level and strongly positive, whereas they were not significant in table 5. In the GPA model, the effect of attitudes is consistent with that estimated previously, while the one and two parent high categories are significant compared to the one parent low and high significant categories from table 6.

In all, the conclusions remain. Family college expectations are estimated to significantly impact own-attitudes and spill-over effects continue to be present from changes in those expectations. As before, some evidence still exists for family college expectations to directly impact GPA. Peer attitudes impact own-attitudes and peer GPA impacts own-GPA. Again, own-attitudes in turn have an affect on GPA that is both direct and spills-over across a school network. Thus, changes in parental ideals (proxied by college expectations) impact performance through their im-

pact on attitudes. These conclusions from using the undirected graph are consistent with the conclusions from using the directed graph.

6.3 Summary of Results

Own-attitudes about school are strongly affected by parental college expectations and peer attitudes. Families play a role in producing attitudes. In the theory, this was modeled by family transmission of ideals entering the production function for attitudes and motivated by the skill development literature—reviewed in chapter two—which shows that noncognitive skills are malleable into young adulthood. Moreover, the partial effects for the own-attitudes model showed evidence for spill-overs from changes in family expectations. These spill-overs work partially through the presence of an estimated social multiplier effect. The social multplier effect occurs because average peer attitudes are estimated to have a positive impact on own-attitudes. Thus, as family educational expectations change an adolescent's attitudes are affected and through their links in the school network those effects can spread.

Effort in school is proxied by GPA. Average peer GPA is estimated to have a strong, positive relationship with own-GPA. The estimate for GPA peer effect is in line with those from previous studies employing the Add Health data. Own-attitudes is estimated to have a significant positive effect on GPA. This effect is as strong as the estimated effect from the ability proxy. A change in own-attitudes is also estimated to have a spill-over effect on the GPA through social links in a school network. Family expectations are estimated to have some small effects on GPA, but it appears that the family ideal effect works more through attitudes than through conforming effects directly to GPA. Overall, families and peers affect performance in school through their impact on own-attitudes and directly through other channels. The theory allowed for a conforming channel seperate from own-attitudes. The evidence here is largely consistent with the theory.

Table 13. Partial Effects for Attitudes and GPA Models with the Undirected Graph

	D.V. = Attitudes			D.V. = GPA		
	Direct (SE)	**Indirect** (SE)	**Total** (SE)	**Direct** (SE)	**Indirect** (SE)	**Total** (SE)
Attitudes				0.187*** (0.017)	0.151*** (0.014)	0.338*** (0.031)
Two Parents in Low Category	-0.348*** (0.073)	-0.315 (0.212)	-0.663*** (0.217)	-0.029 (0.062)	-0.222 (0.168)	-0.252 (0.176)
One Parent in Low Category	-0.149** (0.059)	-0.376** (0.167)	-0.525*** (0.172)	-0.067 (0.050)	0.011 (0.144)	-0.056 (0.151)
One Parent in High Category	0.104** (0.048)	0.260* (0.146)	0.364** (0.148)	0.087** (0.041)	-0.167 (0.116)	-0.080 (0.122)
Two Parents in High Category	0.257*** (0.051)	0.257* (0.156)	0.515*** (0.158)	0.109** (0.045)	0.046 (0.127)	0.154 (0.134)
Picture Vocabulary Test Scores	0.001 (0.021)	0.063 (0.045)	0.064 (0.046)	0.150*** (0.016)	0.088** (0.043)	0.238*** (0.044)
Feel Other Students are Prejudiced	-0.071*** (0.014)	0.028 (0.038)	-0.043 (0.039)	0.014 (0.011)	-0.026 (0.032)	-0.011 (0.034)
Highest Parental Education	0.005 (0.008)	0.078*** (0.019)	0.083*** (0.019)	0.026*** (0.006)	0.029* (0.016)	0.055*** (0.017)
Single Parent Household	-0.084* (0.046)	0.164 (0.137)	0.080 (0.144)	-0.019 (0.039)	0.068 (0.111)	0.049 (0.117)
Number of Siblings in Home	0.002 (0.014)	0.039 (0.036)	0.041 (0.036)	0.005 (0.012)	0.053* (0.031)	0.058* (0.032)
Female	0.086** (0.036)	0.007 (0.087)	0.093 (0.079)	0.215*** (0.030)	0.020 (0.072)	0.234*** (0.067)
Hispanic	0.114 (0.093)	-0.067 (0.191)	0.047 (0.181)	-0.075 (0.072)	-0.083 (0.155)	-0.158 (0.152)
Asian	0.067 (0.114)	0.034 (0.196)	0.100 (0.166)	-0.015 (0.090)	0.008 (0.156)	-0.008 (0.143)
Black	0.062 (0.119)	-0.022 (0.182)	0.040 (0.149)	0.124* (0.095)	-0.290* (0.153)	-0.165 (0.132)
Spanish Spoken in the Home	-0.003 (0.077)	0.453** (0.177)	0.450** (0.174)	0.133** (0.068)	0.310** (0.156)	0.443*** (0.155)
Other Language Spoken in the Home	-0.054 (0.094)	0.415** (0.196)	0.361** (0.184)	0.064 (0.077)	0.352** (0.163)	0.416*** (0.163)
School Grade	0.043 (0.029)	-0.061 (0.040)	-0.018 (0.023)	0.052** (0.023)	-0.059* (0.031)	-0.007 (0.020)

Note: * p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors are in parentheses and drawn by simulation as noted previously. All models estimated with school fixed effects. Only the GNS model is presented for conciseness. LR tests for models with the undirected graph indicated that the GNS with school fixed effects returns the best fit of the data for both the attitudes and the GPA models.

CHAPTER VII
CONCLUSION

Families and peers matter for adolescent educational success. Families impart expectations for education, which theoretically form ideals for education from the family group. Attitudes about school are malleable and family transmission of ideals shape those attitudes. An adolescent, taking part of a school social network can spread influence from their family's educational expectations through transmission of educational ideals with their peer groups. From an identity point of view, it is the peers an adolescent identifies with that matter most. Changes in attitudes can spread over the school social space through the peer effects created within groups. Attitudes, in turn, impact the amount of effort an adolescent gives in school thereby affecting their performance. Holding attitudes constant, ideals for education among families and peers may also provide a conforming incentive. This can occur if failure to conform with the ideal creates costs by reducing identity utility. In this dissertation, I draw on multiple literatures to frame these insights as research questions, to explore them in a formal theoretical model, to connect the theory with an spatial empirical model, and test the model with network data on adolescents from Add Health.

In chapter 2, I motive my dissertation from the identity, skill development, and peer effects literature and I contribute to the literature itself by synthesizing new research questions from them. Those questions are as follows: does family influence reach across networks through the presence of peer effects? Do social group effects create lasting influences? If so, is it through a conforming effect or a production of lasting traits? This dissertation has been in service to studying the first question. The remaining questions set forward a research agenda and motivate future work for the field.

Chapter 3 provides a theoretical treatment. I first explore a model of conflict between one's personal identity, or simply own tastes, and group ideals. The group offers benefits not avail-

able on the market. A person may move closer to their group to gain these benefits. Moving closer to the group necessitates conformity. A person who does not agree with the prescribed actions is faced with a tradeoff between utility from fulfilling their own tastes and benefits derived from the group. In the case of interventions, a treated individual may show agreement with the intervention yet do otherwise if it conflicts with their group and no replacement for the group benefits can be offered. I extend and expand this model of conflict to the case to two groups—families and peers—and specifically to the choice of effort in school for adolescents. In this framework, I provide a concise model of family and peer inputs to the production of attitudes about school and their provision of conforming incentives for effort. The framework allows families and peer groups to conflict or be similar in their expectations leading to varying incentives for attitudes and effort.

Subsequent chapters introduce the data, methods, and empirical results. The partial effects from a spatial econometric model provide a direct link to the equilibrium condition outlined in the family and peer identity theory and easily allow testing for spill-over effects in a school social network from changes in family expectations and adolescent attitudes. I use parental expectations for college graduation as a proxy for family ideals on education and I use the average outcome of one's chosen peers (friends) to proxy prototypical behavior in the group forming the peer group ideal. In the attitudes model, the average of attitudes in the peer group forms the prototypical attitudes creating peer effects, and in the GPA model, average GPA forms the prototypical behavior.

Studying the spatial partial effects for adolescents in both the attitudes and the GPA models, suggest that families and peers are important to an adolescent's educational attitudes and effort. An adolescent has a malleable characteristic, their attitudes about future education and their current school. Attitudes impact own-performance and the performance of other adolescents in the school. Indeed these effects from attitudes are estimated to be as strong or stronger than the effects from an ability proxy. Families and peers contribute to the formation of attitudes about school and impact performance in school through them. Changes in family expectations generate spill-overs through the presence of peer effects in attitudes. While families appear to mostly influence the adolescent through their attitudes, peers are found to have influence on the attitudes

and directly on performance. The theory allowed for both channels, one that shapes malleable attitudes and another that incentivizes conformity regardless of the adolescent's attitudes. The results are consistent with the theoretical implication that positive changes to family expectations for education (ideals) can not only impact the individual but have strong effects across a school network. Also, positive changes in attitudes among peers can benefit the individual and spill-over improving outcomes in the network.

The results support the theoretical point that family and peer groups can create incentives that combine or compete. The evidence supports the presences of social interaction effects, direct effects from parental educational expectations, and indirect effects from parental educational expectations. Thus, they can combine through the presence of spillovers generated by changes in parental educational expectations working through the social interaction effects holding all else constant. Additionally, because of social interaction effects any other changes working opposite of parental expectations will then create competing effects. These potentials should be taken into account, therefore working with both families and larger groups of adolescents in a school may help avoid competing effects.

For adolescents, it is not too late for diversion from poor outcomes. It is well known in the literature on skill development that adolescents are less movable on cognitive skills but remain malleable on noncognitive skills. The results of this paper suggest ideals on education transmitted from families and peers play a role in the choice of effort. Thus, targeting adolescent attitudes combined with family programs may contribute to strong improvements in attitudes and effort. Shifting adolescent ability may be out of reach, but shifting attitudes through families and peer groups may not be.

There are some limitations of this study. The effect of attitudes on academics is checked in the robustness section and shown to remain consistently positive; however, pinning down causal effects from attitudes about school will benefit from future work with study designs around treatments in school that target attitudes. The role of parental educational expecations, or parental actions in general, may be simultaneously determined with adolescent academic attitudes and perfor-

mance along with other behaviors. I did not disentangle this possible source of bias. Future work should consider this more closely. Missing data in friendship nominations is also a concern. Individuals with all missing nominations are removed from the data. To check against these deleted observations, I checked the results using the undirected graph—with the friendship reciprocity assumed—regaining many of the lost observations. The results were consistent; however, the reciprocity assumption itself may be weak. Finally, I avoid a full panel data treatment with the two periods of high school data that exist. Spatial panel models have been well developed for the situation where the spatial weights matrix does not change over time.[1] The case of a weights matrix that may change over time, such as a social network, is less developed. Therefore, at this time use of cross-sectional data with network data and spatial econometrics has been standard in the literature.

I find spill-overs from studying friendship nominations, implying peer effects from those one identifies with. Of course, sub-groups can exist within a school that are not very well connected. Sub-groups may form around salient features, such as race, ethnicity, language, and so on. If there are no, or few links, between sub-groups, then spill-overs that originate in one sub-group will not reach the other. Network structure will impact the spread of own-attitude shocks in a school network. Future research should consider this point. Knowledge of the spread of attitudes in a network based on network structure can facilitate the design of interventions. Drawing students for an attitudes treatment (if you will) with hopes of creating spill-over effects, may require institutional knowledge of the sub-groups within a school to be affective. My study does not test whether spill-overs are mitigated in the presence of disconnected sub-groups, but it lays the groundwork for future refinements to continue exploring combined family and peer effects.

Multiple extensions to this work are plausible. I do not attempt to uncover differences in the family and peer identity effects across ethnicity or socio-economic status. Future work should study whether spill-overs are broken between sub-groups of highly connected individuals who share few links between sub-groups. In such a case, intervention design will need to draw mem-

1. See Elhorst (2014) for a review.

bers from each group if the goal is to achieve positive spill-overs in the social network. It may also prove fruitful to extend the theory and spatial models used here to study family and peer identity effects among adolescents for other outcomes, such as behavioral problems. Families and peers may play combined roles in the formation of a variety of traits such as team-work, timeliness, and violence (indeed Heckman and Mosso (2014) show that families do), not just schooling attitudes, that are important to a variety of outcomes and spread influence across networks. This paper can also guide future work to investigate policy, field experiments, and intervention efforts in schools around the mechanisms outlined here to provide stronger results on the causal effects of attitudes and ideals. Finally, this paper informs future research design through its exploration of spill-overs. Evaluations of social programs in schools, or any possible network, must be careful because untreated individuals may receive spill-over effects from the treated—even if they are not directly linked—that render them a poor control group.

Family and peer groups form important social influences, and positive changes in social incentives for education occurring in both groups will have significant effects for an adolescent that can spread over schools. Importantly, this suggests that social programs which endeavor successfully to improve ideals on education through improving attitudes about school may have positive influence for the treated and those not treated but linked in the network. Moreover, because families provide a strong influence, programs that work both in the school with groups of adolescents and with the families may achieve stronger outcomes than programs which ignore one or the other.

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